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DUAL LONG MEMORY PROPERTY IN RETURNS AND VOLATILITY: THE EVIDENCE FROM TURKISH STOCK MARKET

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Danışman
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ABSTRACT

Master Thesis

Dual Long Memory Property in Returns and Volatility: The Evidence from Turkish Stock Market

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This study investigates the dual long memory property in the returns and volatility of the Turkish stock market indices, by using the ARFIMA-FIGARCH model. Moreover, we examine the volatility behaviour and persistence in the Istanbul Stock Exchange to provide new and additional evidence on the impact of sudden changes on the persistence in volatility.

The results indicate that ISE100, ISEIND, and ISEFIN indices have long memory in return and in volatility simultaneously. Volatility persistency of all indices except ISEIND is overestimated when break dates are ignored. Thus, researchers studying on volatility should consider the volatility breaks. More importantly, volatility shifts may be the source of long memory in ISE100 and ISEFIN indices.

Double long memory property found in Istanbul Stock Exchange contradicts the weak form market efficiency. Thus future prices can be forecastable, which leads the possibility of speculative gains. In an inefficient market, information handling process regarding past prices along with firm specific and macroeconomic information, such as merger plan announcements, inflation, or unemployment, make it possible to gain abnormal returns. Moreover, techniques using past prices to forecast futures prices, such as technical analysis and charting, may be useful to forecast futures prices. techniques using financial information to search under priced stocks, such as fundamental analysis enable to gain abnormal returns in an inefficient markets, such as Istanbul stock exchange because not only prices are forecastable but also information flow have long run impact on volatility.

Keywords: Dual long memory, volatility, ARFIMA-FIGARCH, Efficient Market Hypothesis, ISE

ÖZET

Tezli Yüksek Lisans Projesi

Getiri Ve Volatilitede Görülen Çifte Uzun Hafıza Özelliği: Türkiye Hisse Senedi Piyasası Örneği

Erdost TORUN

Dokuz Eylül Üniversitesi

Sosyal Bilimler Enstitüsü

İngilizce İşletme Anabilim Dalı

İngilizce Finansman Programı

Bu çalışma Türkiye hisse senedi piyasası endeks getiri ve volatilitelerinde aynı anda görülen çifte uzun hafıza özelliğini ARFIMA-FIGARCH modeli kullanarak incelemektedir. Ayrıca volatilitede görülen ani değişimlerin volatilite sürekliliği üzerine etkisi incelenerek volatilitedeki kırılmaların uzun hafıza oluşumundaki olası etkileri araştırılmıştır.

FIGARCH modeline ilişkin tahmin sonuçları göstermiştir ki İstanbul Menkul Kıymetler Borsası'nda volatilitede meydana gelen bir şokun etkisi uzun sure devam etmektedir. Dolayısıyla, yatırımcılar küresel ya da bölgesel finansal dalgalanmaların etkisinin Türkiye de kısa hafızalı piyasalara oranla daha şiddetli hissedileceğini dikkate almalıdırlar. Ayrıca fiyat değişimlerinde görülen ilişki, dolayısıyla volatilitede uzun hafıza, fiyatlandırma mekanizmasını bozarak dolaylı yoldan etkin piyasa hipotezini geçersiz kılmaktadır. Ayrıca kırılma analizi göstermiştir ki endeksler, küresel ya da sektörel haberler tarafından şiddetli biçimde etkilenmektedir. Dolayısıyla yatırımcılar küresel ve bölgesel gelişmeleri konusunda dikkatli olmalıdır.

İstanbul Menkul Kıymetler Borsası' nda tespit edilen çifte uzun hafıza özelliği zayıf formlu etkin piyasa hipotezini çürütmektedir. Dolayısıyla tahmin edilebilir hisse senedi fiyatları spekülatif kazançlara yol açabilmektedir. Fiyatların tahmin edilebilir olması ve bilgi akışının volatilite üstünde uzun süre etkili olması nedeniyle İstanbul Menkul Kıymet Borsası gibi etkin olmayan piyasalarda; geçmiş fiyatları, birleşme haberleri, enflasyon, işsizlik gibi firma bazındaki ya da makroekonomik bilgileri analiz eden veri işleme teknikleri kullanılarak aşırı karlar elde edilebilmektedir. Teknik analiz gibi geçmiş fiyatlar kullanılarak gelecekteki fiyatların tahminine dayanan yöntemler ile temel analiz gibi finansal bilgileri düşük fiyatlanmış hisse senedi tespiti için kullanan teknikler başarılı sonuçlar verebilmektedir.

Anahtar kelimeler: Çifte uzun hafıza, volatilite, ARFIMA-FIGARCH, Etkin Piyasa Hipotezi, İMKB

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CHAPTER 2

LONG AND SHORT MEMORY MODELS

CHAPTER III

DATA AND EMPIRICAL FINDINGS

ABBREVIATIONS

ADF	: Augmented Dickey–Fuller Test
AGARCH	: Asymmetric GARCH
AML	: Approximate Maximum Likelihood
APARCH	: Asymmetric Power ARCH
ARCH	: Autoregressive Conditional Heteroscedasticity
ARFIMA	: Fractionally Integrated Autoregressive Moving Average Model
ARFIMA-FIGARCH	: Autoregressive Fractionally Integrated Moving Average – Fractionally Integrated GARCH
ARMA	: Autoregressive Moving Average
AS	: Aggregate-Shock Model
ASAR-EGARCH	: Asymmetric Autoregressive Exponential GARCH
BDS	: Brock – Dechert – Scheinkman Test
BGARCH	: Break-GARCH
CBOE	: Chicago Board of Option Exchange
CCRV	: Close-To-Close Realized Volatility
CEE	: Central and Eastern Europe countries
CGARCH	: Component GARCH
DAX	: Deutsche Aktienindex
DCC	: Dynamic Conditional Correlation
DJIA	: Dow Jones Industrial Average
DTGARCH	: Double Threshold GARCH
EGARCH	: Exponential GARCH
EGB2	: Exponential Generalized Beta Distribution of the Second Kind
ESTGARCH	: Exponential Smooth Transition GARCH Model
EWMA	: Exponentially Weighted Moving Average
FED	: Federal Reserve System
FIAPARCH	: Fractionally Integrated APARCH
FIGARCH	: The Fractionally Integrated Generalized Autoregressive Conditional Heteroscedaticity
FIEGARCH	: Fractionally Integrated EGARCH
EU	: European Union

GARCH	: Generalized Autoregressive Conditional Heteroscedaticity
GARCH-M	: GARCH-in Mean
GDP	: Gross Domestic Product
GED	: Generalized Error Distribution
GJR-GARCH	: Glosten-Jaganathan-Runkle GARCH
GPH	: Geweke-Porter-Hudak Procedure
GQARCH	: Generalized Quadratic GARCH
G7	: Group of Seven Countries
HIS	: Historical Volatility
HYGARCH	: Hyperbolic GARCH
ICSS	: Iterated Cumulated Sum of Squares Algorithm
IEGARCH	: Integrated EGARCH
IGARCH	: Integrated GARCH
IID	: The Independent and Identical Distribution
IMF	: International Monetary Fund
ISE	: Istanbul Stock Exchange
ISE100	: Istanbul Stock Exchange National 100 index
ISEFIN	: Istanbul Stock Exchange Financial Index
ISEIND	: Istanbul Stock Exchange Industrial Index
ISESRV	: Istanbul Stock Exchange Services Index
ISETECH	: Istanbul Stock Exchange Technology Index
KPSS	: Kwiatkowski-Phillips-Schmidt-Shin test
LEAPs	: Long-Term Equity Anticipation Securities
LGARCH	: Log GARCH
LMSV	: Long Memory Stochastic Volatility
LM	: Lagrange Multiplier
LSTGARCH	: The Logistic Smooth Transition GARCH
LTCM	: Long Term Capital Management
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percent Error
MCS	: Model Set Confidence Procedure
ME	: Mean Error Root
MMR	: Modified Rescaled Range Test
MSFE	: Mean Square Forecast Errors
NGARCH	: Non Linear GARCH

NAGARCH	: Non Linear Asymmetric GARCH
NASDAQ	: National Association of Securities Dealers Automated Quotation System
NYSE	: New York Stock Exchange
OECD	: Organisation for Economic Co-operation and Development
OPEC	: Organization of the Petroleum Exporting Countries
PP	: Phillips- Perron Test
PRV	: Pseudo Realized Volatility
QGARCH	: Quadratic GARCH
RMSE	: Mean Square Error
RR	: Rescaled Range Procedure
RSGARCH	: Regime Switching GARCH
R/S	: Rescaled Range Statistic
RW	: Random Walk
S&P 500	: The Standard and Poor's
SPARCH	: Semi Parametric ARCH
SPYDER	: Standard & Poor's Depository Receipts
SV	: Stochastic Volatility
SV2F	: Two Volatility Factors Model
SWARCH	: Regime Switching ARCH
TGARCH	: Threshold GARCH
US	: United States
UK	:United Kingdom
VaR	: Value-At-Risk
VIX	: Volatility Index
WFE	: World Federation of Exchanges
WHI	: Whittle Procedure

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INTRODUCTION

Modeling the long memory property in stock market returns and volatility is one of the most prevailing and well documented topics in finance literature. Long memory implying the existence of dependencies among observations due to hyperbolically decaying autocorrelation function seems more realistic than short memory feature associated with the exponentially fast decaying autocorrelation function, which implies the existence of negligible correlation at long lags.

Granger and Joyeux (1980) and Hosking (1981) proposed the fractionally integrated autoregressive moving average (henceforth ARFIMA) model to capture long memory pattern in the conditional mean. The ARFIMA model allows the integration order of the conventional autoregressive moving average (henceforth ARMA) model to take non-integer value between 0 and 1. A vast literature has focused on investigating long memory in returns via ARFIMA models. Empirical studies get rather mixed results for developed and emerging markets. In contrast to the studies of Sadique and Silvapulle (2001), Byers and Peel (2001), Henry (2002) and Gil-Alana (2006) finding significant evidence in favor of long memory in developed markets; Lo (1991), Crato(1994), Barkoulas and Baum (1996), Jacobsen (1996) and Tolvi (2003) find significant evidence against long memory in these markets. Many studies, including Barkoulas et al(1996), Berg and Lyhagen (1998), Sadique and Silvapulle (2001), Wright (2001), Panas (2001), has focused on memory pattern in emerging markets and showed these markets exhibit long memory feature. However, among others, Berg and Lyhagen (1998), Resende and Teixeira (2002), Limam (2003) found significant evidence in favor of short memory.

In recent years, modeling long memory in volatility has attracted great deal of attention from finance literature. After Ding et al (1993) showed the slowly diminishing autocorrelation function of squared daily stock returns, many studies have been investigated memory pattern of volatility. Among others, Bollerslev and Mikkelsen (1999), Maheu (2002), Caporin (2003), Ñíguez (2003), Kang and Yoon (2006), Wang and Hsu (2006), Brandt and Jones (2006), Bhardwaj and Swanson (2006), Gospodinov et al (2006) have investigated the long memory property of volatility in developed markets. Also relatively small number of studies including Lee et al (2000), Kilic (2004), Gandhi et al (2006), Cheong et al (2007), Kang and Yoon (2007), Hatgioannides and Mesomeris (2007), Floros et al (2007) have focused on the memory pattern of volatility in emerging markets. To detect the memory pattern in volatility, Ballie et al (1996) introduce the fractionally integrated generalized autoregressive conditional heteroscedaticity (henceforth FIGARCH) model by extending the IGARCH model through allowing for persistence in the conditional variance. GARCH and IGARCH model have memory which is much shorter than that of generally financial series have. Thus, the shortcoming of exponential decay for the correlation of the squared return in GARCH and IGARCH model is eliminated.

The existence of long memory in returns putrefies the weak form market efficiency hypothesis stating that future asset returns are unpredictable through past returns. However, long memory implies that future returns are affected by its predecessor due to dependency among distance returns, which leads progressive respond to information flow and the possibility of consistent speculative profits. Due to higher average return and low correlation with developed markets, emerging markets are important for global investors implementing portfolio diversification strategies. However, the common features of emerging markets including, higher and persistent volatility, market thinness, nonsyncronous trading, rapid changes in regulatory framework, and unpredictable market response to information flow lead the existence of long memory. Hence, modeling the long memory in return and volatility has become an integral part of risk measurement and investment analysis in these markets.

A literature proves that occasional breaks, switching regimes, and structural changes have significant effects on generating long memory characteristics. Hyung et al (2006) and Granger et al (2004) examine the Standart and Poor’s (henceforth S&P 500) index and find that occasional breaks could be responsible for evidence of long memory. Diebold and Inoue (2001) perform Monte Carlo analysis and find that the presence of regime switching is capable of producing the long memory property. Mikosch and Starica (2000) prove that structural changes may cause long memory in S&P index. Hence, we investigate the effects of multiple unknown structural breaks on long memory. Volatility is highly persistence when a shock to a given system is permanent. In this case, an integrated GARCH (henceforth IGARCH) model proposed by Bollerslev and Engle (1996) can be used. However, the major domestic or global economic and political events make stock prices be unstable, and these major events could lead to sudden changes in volatility, and hence can affect its persistence. Lamoureux and Lastrapes (1990) reveal that volatility persistence may be overstated if structural breaks in parameters are not introduced to a standard GARCH model. If structural breaks occur in series, then estimates of coefficients will not be accurate and forecasting based on these estimates is also affected in GARCH process. Lastrapes (1989) applied the autoregressive conditional heteroscedasticity (henceforth ARCH) model to exchange rates and found that there is a significant decrease in the estimated volatility persistence when monetary regime shifts are incorporated in a standard ARCH model. However, those monetary regime shifts were exogenously determined. Imposing regime shifts exogenously may introduce serious biases into the analysis (see Malik, *et al*., 2005).

Inclan and Tiao (1994) proposed the iterated cumulated sum of squares (ICSS hereafter) algorithm to detect structural breaks (sudden changes) in the variance of a financial time series. The main feature of this algorithm is that it determines breakpoints in variance endogenously. Moreover, the ICSS algorithm is capable of detecting significant increases and decreases in volatility so that both the beginning and the end of distinct regimes may be detected. Aggarwal *et al*. (1999) applied the ICSS algorithm to emerging markets for the period between 1985 and 1995, and found that most events leading to volatility shifts tended to be local and that the only global event over the sample period that affected several emerging markets was the October 1987 stock market crash in the US.

The purpose of this thesis is to investigate the dual long memory property in the returns and volatility of Turkish stock market, one of the emerging markets on which little research have focused, by using the autoregressive fractionally integrated moving average – fractionally integrated GARCH (henceforth, ARFIMA-FIGARCH) model, which is unique to capture the long memory in return and volatility simultaneously. Moreover, the distributional properties of stock returns are also investigated in this paper. Finally, we investigate the volatility behavior and persistence in the Istanbul Stock Exchange (hereafter ISE) to provide new and additional evidence on the impact of sudden changes on the persistence in volatility.

This thesis is formed by three parts. First chapter focuses the types, characteristics, and determinants of the volatility. Also long memory property among returns and Efficient Market Hypothesis is discussed. Second chapter consist comprehensive literature reviews of long and short memory in volatility models. Empirical analysis results are discussed in chapter three.

The thesis provides the following contributions to the literature:

This thesis gives a comprehensive volatility analysis to model the volatility of the Istanbul Stock Exchange. Volatility of ISE is attempted to model through a number of short and long memory volatility models, including APARCH and ARFIMA-FIAPARCH. It provides a very comprehensive literature on volatility models.

To the best of our knowledge, this is the first study which uses double long memory model of ARFIMA-FIGARCH to analyze double long memory and finds double long memory in ISE. Also volatility breaks and their impact on volatility persistence are investigated through ICSS algorithm.

Finally this thesis evaluate weak form of efficient market hypothesis in terms of long memory in ISE

CHAPTER I

VOLATILITY

This chapter summarizes the definition, properties, and variants of volatility. Moreover, the impact of volatility on the economy and the use of volatility in finance are explained. Also main determinants of volatility are discussed. Also, in terms of return, the consequence of long memory on market efficiency is discussed. Thus, a brief literature on market efficiency and a brief overview of both Turkish economy and finance market is presented in this chapter.

1.2 Risk, Uncertainty, And Volatility

Contrary to common belief, risk and uncertainty are distinct terms. Knight (1921) argued the risk and uncertainty. He argues that although uncertainty is defined as situations in which the decision-maker can not assign probabilities to events because of impossibility to calculate chances, risk denotes the situations in which the decision-maker imposes probabilities to choices on the basis of 'known chances'.

In financial markets, the risks attached to the stocks can be generally grouped into systematic and unsystematic risks. While systematic risk arises due to macroeconomic variables and can not be diversifiable, firm level factors produce unsystematic risk, and adding different stocks into portfolio can diversify away the unsystematic risk. More specifically, Cuthbertson and Nitzsche (2001:566) classifies the main risk types are legal risk, liquidity risk, credit risk, operational risk, assimilation risk, incentive risk, market risk, and model and estimation risk. Legal risk is the risk of a contract not enforced as expected. Liquidity risk may arise due to lack of counterparty to trade within the time scale desired. The lack of funds available by the counterparty who then defaults leads credit risk. Operational risk may originate through mishandled origination, settlement and clearing of trades. Traders or other participants who do not fully understand how assets are priced and the risks taken are the reason of assimilation risk. Remuneration packages encouraging excessive risk taking increases incentive risks. Change in asset price level produce market risk. Model and estimation risk stems from choosing the wrong model or the wrong estimation technique to estimate the risk models (Cuthbertson and Nitzsche 2001:566)

Volatility is the variance, or standard deviation of a given variable. Although volatility can be calculated from any irregular distribution, it can be used as a measurement of risk only if it is assumed that time series are normally distributed. Fama (1965) is one of the first researchers to evaluate stock price changes and argues that the most important factor to evaluate the risk of investment in stocks is the shape of the distribution. Moreover, the shape of the distribution helps to evaluate the nature of the process generating price changes. He also states that the distribution assumptions strongly affect the relative importance of volatility, such as volatility should not be used in researches under the Paretian distributions of stock prices.

Schwert (1989) investigates the properties of volatility and finds that financial instrument returns and economic variables become more volatile during recession periods. Moreover, financial instrument volatility may play an important role in predicting future macroeconomic volatility since information flow about economic events lead movement on prices of speculative financial instruments. He also finds that stock volatility are affected by financial leverage. Stock volatility decreases if stock prices rise relative to bond prices. Finally, he states that both share trading volume growth and the number of trading days in the month is positively related to stock volatility.

In another important research, French, Schwert and Stambaugh (1995) find significant evidence in favor of positive relation between the predictable level of volatility and the expected risk premium of a financial instrument. Also they argue that negative unexpected change in volatility decreases future expected risk premiums and raises current stock prices. Hence, it is evidence that there is negative relation between the unpredictable component of stock market volatility and realized risk premiums. Also market volatility has an impact on the motivation to save and to invest.

Becketti and Seldon (1989) argue that financial market volatility distorts the economic performance through damaging smooth functioning of the financial system, which leads regulatory changes about the financial system. A sharp fall in stock prices reduces wealth of investors, hence consumer spending is affected. Stock market volatility primarily affects business investment spending and consumer spending in an economy. Since the volatility is considered as a sign of increasing risk, funds are channeled towards less risky assets, which results in higher cost of capital. Moreover increasing volatility puts additional brunt to small and new firms via the fund shifts to larger well-known corporate stocks. Hence investment choices are intensely affected by volatility. Moreover, economic growth decreases through decreasing business caused by financial market volatility. One of the leading economic performance indicators is equity market prices. Higgins (1988) state that since the discounted value of expected future business profit determines the long run stock market price, an expectation of decrease in future profits may lead stock market prices to fall. Most important effect of increasing volatility on the economy is discredited consumer confidence, which leads even non investors to reduce their spending. Also economic growth is reduced via the decrease in consumer consumption. Thus reduced investor confidence and liquidity are the results of high volatility periods in an economy. Furthermore, volatility decreases trading volume through the detraction of risk averse investors.

1.2 Types of Volatility

Generally, volatility can be calculated based on four types: historical, implied, deterministic, and stochastic volatility. Past observations are used to calculate historical volatility and this type of volatility is typically employed to design option pricing models. Although using historical volatility provides less precise option validation, it gives efficient evaluation results of forecasting ability of complex time models (Brooks, 2002; 441). Akgiray (1989) evidenced that conditional heteroscedastic processes, such as GARCH (1,1) model, give more accurate forecast of variance than that of historical volatility. He also argues that historical volatility is insufficient to describe the volatility pattern. Moreover, since traders use ax ante (rather than ex post) variances to form expectations of return, GARCH forecast of variance is better than historical variances through improved parameter estimations. The assumption of historical volatility that future volatility equals to past volatility is putrefied by vast literature.

Implied volatility is the volatility over the life time of the option implied by the valuation of the option. It is calculated by numerical procedures, such as the method of bisections, on option valuation models (Brooks, 2002; 442). Duarte and Fonseca (2002) argue the implied volatility is the predicted volatility of the underlying asset of an option for the remaining time to the maturity. Inclusion of the market's general opinion about the asset volatility is the most important feature of implied volatility.

Duarte and Fonseca (2002) argue that deterministic volatility can be calculated by using historical volatility on a given function or models, such as ARCH and GARCH. Deterministic volatility calculation makes it possible to forecast future volatility. They further argue that the distributional properties of fat tail, high frequency of extreme values, and non-normality lead to the assumptions of stochastic volatility, which volatility is a random process different than the one that drives asset prices, although the two of them may be correlated and this random process affects the behavior of returns and volatility. Schmalensee and Trippi (1978) evaluate the forecasting performance and find significant evidence that the implied volatility provide more accurate volatility forecasts than the estimates made with the standard deviation of past returns. Brooks (2002) states that the disadvantage of stochastic volatility that computational complexity in the process of estimating parameters reduces its popularity in empirical discrete-time financial studies.

1.3. Volatility in Finance Literature

Volatility is a crucial factor in finance since it is widely used in option pricing, value at risk formulation, asset allocation under the mean-variance framework, and improving efficiency of parameter estimation and forecasting performance. Moreover, the volatility index, the VIX, launched by the Chicago Board of Option Exchange (hereafter CBOE) shows that volatility becomes a financial instrument (Tsay, 2005; 98). In recent years, persistence of volatility plays an important role to make inferences about the effect of shocks on financial series

The variance is associated with risk and uncertainty in the finance literature. The four moments of financial time series are mean, standard deviation, skewness, and kurtosis. Poon and Granger (2005) argue that since the assumption of normally distributed variable in the capital asset allocation model and markowitz mean-variance portfolio theory leads the skewness and excess kurtosis be zero; the two moments, mean and standard deviation, is adequate to calculate and make inferences about the descriptive statistics of normal distribution of a given time series. However it is proven that distribution of the financial time series all over the world is not Gaussian normal; Moreover, negative price movements are extremely more important than positive price movements in terms of measuring potential loss in a given possibility. Hence, Value-at-risk (hereafter VaR) becomes a widely used risk measurement technique. In VaR, quintiles are estimated through standard deviation of a time series, which indicates that standard deviation plays a key role in risk measurement.

In option pricing, implied volatilities based on Black Scholes formula and at-the-money options are widely used. According to the Black Scholes formula, variance of the stock is the most essential factor to determine option price and to infer future option volatility. It is evidenced that forecasts via implied volatility are more accurate than that of historical volatility. However, implied volatilities cannot be used simultaneously in terms of pricing the derivatives whose prices are calculated under the time constraints. Hence, time-series models are the major source of volatility forecasts.

1.4. The Characteristics of Financial Market Volatility

Common characteristics of financial market volatility seen in financial markets are clustering, persistence, and stationarity. Although volatility clustering which indicates that high volatility tends to follow high volatility and vice versa can be modeled by both short and long memory models, volatility persistence denoting significant autocorrelation over 1000 lags can be modeled by long memory models more efficiently. Other volatility characteristics observed in some financial markets are asymmetry and existence of rare volatility jumps. Different responses of some financial markets to the price increase and decrease leads asymmetry, or leverage effect in volatility. Along with outliers and extreme values, volatility jumps are seen in the periods of crises or policy changes in some financial markets.

In recent years, the effect of volatility shifts on volatility persistence has become an appealing research topic since the volatility shifts reduces estimated volatility persistence. Thus the results of volatility models ignoring volatility shifts may be misleading.

Hsu and Miller and Wichern (1974) start not only an investigation on detecting changes of variance, but also a literature on this subject. They put forward a normal probability model having a nonstationary variance exposed to step changes at uneven time points, albeit in previous investigations nonnormality of the stock returns are indicated, and using the heavy tailed distribution is recommended. In addition to Booth and Smith (1982) conducting a study on the existence of one variance shift by means of Bayes ratio, Worsley (1986) examines one variance shift via maximum likelihood method. Baufays and Rasson (1985) focus on multiple variance breakpoints by estimating with maximum likelihood method. Tsay (1988) discusses ARMA models to detect outliers and variance breakpoints and put forward an outline to determine variance shifts.

The most famous research on volatility breaks is Aggarwal, Inclan and Leal's (1999) work named "Volatility in Emerging Stock Market". They conduct a study about determining the importance of global or local events in causing major shifts in emerging stock markets' volatility. They also investigate whether these events are likely to be social, political, or economic by way of after detecting shifts in volatility. They analyze Hong Kong, Singapore, Germany, Japan, the UK, the US as well as ten of the largest emerging markets in Latin America (Argentina, Brazil, Chile, and Mexico) and Asia (India, Malaysia, Philippines, South Korea, Taiwan, Thailand), also Morgan Stanley indices of the World, the Far East, the Latin America, and the Emerging Market.

Aggarwal, Inclan and Leal (1999) state that the numerous unforeseen changes in the variance are the properties of emerging markets. They use ICSS algorithm and find numerous breakpoints in the variance of stock market indices. According to the results of the study, the October crash makes the series of Mexico, Malaysia, Hong Kong, Singapore, the UK, the US, the World Index, and the Far East Index to have a volatility change. However, the indices of Taiwan and Thailand experience variance breakpoints via local events along with the stock market crash.

The Gulf War gives rise to volatility shifts in Singapore, Japan, the U.S., as well as the World Index, and the Emerging Market Index, but in none of the individual emerging markets. Finally, they conclude that local political events lead to significant variance shifts in stock markets.

Viviana (2005a) investigates the effect of eruption of the Asian Crisis in 1997 and terrorist attacks of September 11, 2001 via the iterated cumulative sums of squares (the ICSS) algorithm and wavelet analysis on stock markets of Emerging Asia, Europe, Latin America, and North America. After filtering four return series of Europe, Latin America, and North America stock indices by way of GARCH (1,1) model to eliminate serial correlation and conditional heteroscedasticity, the ICSS algorithm are used, and breakpoints in August 1997, October 1997, February 1998, and October 1998 are found for Emerging Asia. For Latin America, the ICSS algorithm detects the breakpoints in October 1997, October 1998, February 1999, and June 2000. For North America, breakpoints in October 1997, October 1998, May 2002, and October 2002 are detected. Finally, the ICSS finds the breakpoints in October 1997, April 1998, October 1998, January 2000, September 2001, and October 2002 for Europe.

Viviana (2005b) also conducts a study to account for the effect of political confusions in the Middle East, mostly because of the Iraq War, on some selected Middle Eastern, African and Asian countries (Turkey, Israel, Morocco, Egypt, Jordan, Pakistan, Indonesia), developed countries (the United Kingdom, Germany, Japan, the United States, Japan), and four international indices (Europe and Middle East, Latin America, the World, and Emerging Markets) by means of GARCH (1,1) filtering and the ICSS algorithm and wavelet analysis. After filtering stock returns in US dollars by using GARCH (1,1) model, Viviana (2005b) concludes that the only stock market of Turkey appears to be affected by the beginning of the Iraq war because of the significant variance breakpoint at 17 March 2003. However, the terrorist attacks of 11 September 2001 only seem to have had an impact on Jordan's stock market since there are significant variance shifts in 8 August 2001 and 28 September 2001. Indonesia experiences a variance change point in 25 September 2002 and 9 October 2002, the date of the terrorist attack on Bali. Israel's safety barrier causes not only violation of international laws but also a variance shift for Israel in 4 July 2003. Finally, the assassination of the head of Hamas Izzeldin-El

Kassam Brigades makes Europe and Middle East's stock markets to have a significant variance break point in 25 July 2002.

Hammodeh and Li (2008) investigate sudden changes in volatility of Bahrain, Kuwait, Oman, Saudi Abu Dhabi stock market indices from 15 February 1994 to 25 December 2001. They find that, rather than local political events, major global events such as the 1997 Asian crisis, the collapse of stock prices in 1998 after the crisis, the adoption of the price band mechanism by Organization of the Petroleum Exporting Countries (hereafter OPEC) in 2000, and the 11 September attack have significant effect on the Gulf markets. Moreover, they prove the effect of modeling variance shifts in GARCH model on decreasing the volatility persistence.

Wang and Moore (2007) analyze volatility breaks in weekly index returns of Poland, Czech Republic, Hungary, Slovenia, and Slovakia from 1994 to 2006. They find that local political events lead the variances to shifts; Moreover, Break-GARCH (hereafter BGARCH) model significantly reduces the volatility persistence.

Wang and Thi (2006) use the ICSS algorithm as a step of testing contagion effect between Taiwan and US stock indices consisting Taiwan Weighted stock Index and US three big composite indices: New York Stock Exchange (henceforth NYSE) composite index, S&P 500 composite index, and National Association of Securities Dealers Automated Quotation System (henceforth NASDAQ) composite index covering the period from 1 January 1997 to 31 October 2001. They analyze the contagion effect via a process including three steps. First, the ICSS algorithm is employed to detect breakpoint dates. Second, they estimate the exponential GARCH (henceforth EGARCH) model of conditional generalized error distribution, GED-EGARCH, incorporated with dummy variables for breaks the ICSS detected, and calculate dynamic conditional correlation coefficients of Dynamic Conditional Correlation (hereafter DCC) multivariate GARCH model. Finally, contagion effect is checked through one step and N-step forecast tests. Six breakpoints in the unconditional variance of stock return for Taiwan weighted stock index and NYSE composite index, seven breakpoints for S&P 500 composite index, and twelve breakpoints for NASDAQ composite index were detected. They come up with the existence of contagion effect between Taiwan and US stock markets via forward forecasting tests.

Malik, Ewing and Payne (2005) display the fact that using the ICSS algorithm reduces the volatility persistence. This fact contradicts the previous researches stating that financial markets have highly persistent volatility. They uses GARCH(1,1) for modeling volatility and the ICSS models for identifying time periods of sudden changes in volatility by examining weekly Canadian stock market (Vancouver Stock Exchange and Toronto Stock Exchange) data from June 1992 through October 1999. They find one change point making two distinct volatility regimes for Vancouver Stock Exchange while two change points corresponding to three regimes were found for Toronto Stock Exchange. They incorporate these change points in GARCH (1,1) model and show that volatility persistence is significantly reduced.

1.5. Determinants of Volatility

Vast finance literature tries to determine possible sources of volatility. The factors of arbitrage trading, portfolio insurance, insider trading, program trading, spillover effect, news impacts, and macroeconomic factors are considered as the possible determinants of volatility.

1.5.1. Derivative Markets and Volatility

A theoretical framework suggests that derivatives markets, thus arbitrage trading, effect the corresponding spot market volatility. Arbitrageurs gain profit via buying stocks whose price is expected to fall, and selling futures with higher prices simultaneously to take advantage of the price differences. Contrast to exponents suggesting volatility in spot market decreases through speculation in derivative markets, opponents argue that especially speculations increase volatility and destabilize the price fluctuations. According to the exponents, promoted trading activities based on market wide information due to low firm specific information asymmetry in derivative markets lead to more efficient information impound and evaluation process, thus to decreased volatility. However, the opponents declare that arbitrage trading or speculation to gain short term gains through trading in spot and derivative markets exacerbate uncertainty and volatility (see Kyriacou and Sarno (1999) for details).

Bessembinder and Seguin (1992) investigate the relationship between stock market volatility and futures trading volume along with open interest. Consistent with the theory indicating that equity futures trading improves the liquidity and depth of the equity markets, they find that futures trading activities and open interest decrease the equity market volatility. Moreover, they state that stock market volatility is not affected by the futures life cycle. Gulen and Mahyew (2000) investigate the impact of futures trading volume and open interest on spot market volatility for a large cross section of twenty five markets. They state that futures trading activities lowers the spot market volatility except for only Japan and the US. Robinson (1993) investigates the relationship between the futures market and London stock exchange between 1980 and 1983 and proves the reduction of volatility with respect to introduction of futures trading. Kim *et al* (2004) conduct a study on investigating relationship between spot market volatility and futures as well as option contract activities. While they fail to accept the hypothesis of negative relationship between the stock market volatility and the volume for both futures and options contracts, they find a positive relationship between open interest and volatility. Hence, they conclude that while speculative trading activities increase the underlying stock market volatility, hedging activities stabilize the cash market.

Lee and Ohk (1992) conduct a study on possible effects of futures trading on spot markets of Australia, Hong Kong, Japan, the UK and the US. They evidenced that while Hong Kong stock market volatility decreased after the introduction of futures trading; Japan, the UK and the USA stock markets volatilities are increased through futures market. Bologna and Cavallo (2002) study the futures trading effect on Italian stock market volatility and state that futures market has reduced the spot market volatility, hence, they conclude that a developed futures market improves the market efficiency of the corresponding stock markets. Drimbetas et al (2007) signify that derivative trading has reduced the Greece stock market volatility and increased the market efficiency. They also state that speculations through stock index futures decrease the stock market volatility. Pericli and Koutmos (1997) find significant evidence that futures trading significantly reduces the volatility of S&P 500 index for the period spanning from 1953 to 1994 through asymmetric volatility model, namely EGARCH. Pilar and Rafael (2002) examine the impact of derivative trading on the Spanish stock market data spanning 1990 to 1994 by means of asymmetric volatility models and find the significant decrease in spot market volatility through after the introduction of the futures market. Lafuente (2002) investigates intraday volatility interactions between Spanish futures and spot markets for the period 1993 to 1996 via bivariate GARCH model. the findings of positive correlation of current spot market volatility with that of previous futures market indicates that futures market volatility is the destabilizing force behind the volatility of the spot market.

Baklaci and Tutek (2006) observed a significant decrease in Turkey stock exchange volatility after the introduction of futures trading through accelerated information transmission to spot market in their analysis for the period 2004 to 2006. Similarly, Kasman and Kasman (2008) research the impact of introduction of the futures market on Turkish stock exchange for the period 2002 to 2007 through asymmetric volatility models. Beside the interesting result that spot market granger causes futures market but not vice versa, indicating change in spot price effect price level of futures, they declare that introduction of futures market decreases the volatility of Turkish stock exchange. Thus, it is concluded that the futures market in Turkey may stabilize the spot market through expanding the investment opportunity set, improving the daily operation of the market and information efficiency.

Some studies find that impact of the introduction of the derivative markets on corresponding spot market exhibits country specific character. Among others, Harris (1989) analyzes the properties of cash stock market and finds the volatility raising effect of the introduction of the derivatives market on spot market volatility. Moreover Australia stock market seems unaffected by the futures market. Hence it is concluded that the effect of futures trading on volatility changes across countries. Antoniou, Holmes and Priestley (1998) conduct a study on the possible effect of futures trading on the corresponding spot markets of Germany, Japan, Spain, Switzerland, the UK, and the US. While volatility-decreasing effect is found for only Germany and Switzerland, they conclude the existence of neither increasing nor decreasing effect of futures on spot market volatility.

Some studies on the spot market, including Edwards (1988a, b), and Aggarwal (1988) analyzes futures trading and point out that futures trading in the US has no significant effect on volatility, rather macroeconomic factors such as trade deficits, exchange rate movements are likely to be the main source of volatility.

Becketti and Roberts (1990) examine the futures trading activity in the US for the period 1962 to 1990 and find that the volatility of the stock market is independent from futures trading. Board, Sandman and Sutchliffe (2001) study the effect of futures market volume on London stock exchange volatility through the stochastic volatility model for the data covering the period from 1988 to 1995. They find no destabilizing effect of futures trading on spot volatility; Moreover, they provide evidence that the factors of spot trading, or change in volume of spot and futures volatility do not alter the volatility level. Illueca and Lafuente (2003) examine the effect of futures trading on jumps of volatility of the Spanish spot market. They find no evidence that jumps on volatility is a result of futures trading activity. Darrat and Rahman (1995) exemplify the fact that neither futures trading nor macroeconomic factors, such as risk premium or inflation are the force behind episodes of volatility changes in S&P 500 index for the period between May 1982 and June 1991. Instead, they prove significant evidence supporting the volatility-raising effect of term structure and OTC composite index volatilities.

Pok and Poshakwale (2004) analyze the effect of futures trading on volatility and they interestingly reveal that the introduction of derivative trading increases the corresponding Malaysian stock market volatility. Also Ryoo and Smith (2004) examine the relationship between the futures market and Korean stock market, and come up with the conclusion that stock market volatility increases via futures market. They voice that futures market increases the information speed; hence stock market volatility is affected by futures trading.

Some researches focus on the impact of option trading on spot market volatility and find the stabilizing effect of the option markets. Damodaran and Subrahmanyam (1992) exert a survey about the effect of introduction of options to stock market volatility and find the reducing effect of option listing on stock market volatility. Chatrath, Ramchander and Song (1995) analyze whether option trading is the reason of volatility in S&P 500 index volatility for the period between 1984 and 1993. They prove the existence of the stabilizing effect of option trading on spot market volatility. Chaudhury and Elfakhani (1997) provide empirical evidence that option listing stabilizes the spot market volatility through the provision of market liquidity in the Canadian stock market for the period 1975 to 1990. Also they state that option listing is the force behind the decreasing noise trading and accelerated stock price adjustment movement to the new information arrival. Sahlström (2001) exemplifies the fact that stock market volatility decreased significantly with respect to the introduction of the option market in Finland through lower bid-ask spread, quickened price adjustment, and decreased noise effect.

There are a number of studies indicating that option trading destabilizes the spot market. Mahyew and Mihow (2000) examine the relationship between option listing and corresponding spot market volatility in the US for the period 1973 to 1996. They find significant evidence in favor of the hypothesis that option listing is the force behind the increase in volatility. Poon (1994) conducts a study on the possible effects of CBOE option listing on the underlying US stock market returns and volume between 1982 and 1985. It is evident that volatility increase with respect to the introduction of option listing, which indicates improved stock market efficiency, leads stock return volatility to decrease. Also the finding that there is a decaying relationship between stock return volatility and stock volume confirms the hypothesis that options provide investors with a more cost effective medium to trade information, particularly private information.

However some studies find contradictory evidence to Damodaran and Subrahmanyam (1992), such as Bollen (1998) fails to accept the hypothesis that option listing has a significant effect on the US stock market. Also Kabir (1999) examines whether option listing has a significant effect on the Dutch stock market volatility and find no significant effect of option listing on stock volatilities. Mazouz (2004) exerts a study on the relationship between CBOE option listing and NYSE volatility for the period 1973 to 2001 and finds no effect on option listing on volatility. Hence, volatility neutral characteristic of option listing requires no attention about the possible volatility effect. Rahman (2001) investigates the possible impact of Dow Jones Industrial Average (hereafter DJIA) futures and futures options on intraday volatility of corresponding component stocks and finds that introduction of the derivatives instruments unchanges the volatility; thus, no evidence in favor of destabilizing effect of derivatives has been found in NYSE.

In sum, the effect of arbitrage trading through derivatives markets has a country specific character. The study of Kasman and Kasman (2008), and Baklaci and Tutek (2006) indicate that introduction of the futures market is the force behind the reduction of spot market volatility in Turkey. Hence Turkish derivative market stabilizes the underlying spot market.

1.5.2. Program Trading and Volatility

Another possible factor affecting volatility is program trading. Program trading denotes an organized program of trading many securities simultaneously. One of the aims of program trading is to mimic an index in a stock exchange. Also fund managers, such as pension fun managers, use program trading to alter their position and to lock in capital gains in case of decreases in market value. The main critic of program trading is that program trading, particularly index arbitrage program, conveys the excess volatility from the futures markets and shifts liquidity from the cash market, which results in an increase in the intraday volatility and a decrease in liquidity.

Harris, Sofiano and Shapiro (1994) states that the effect of program trading on stock volatility increase may be spurious due to bid-ask bounce and non-synchronous trading. Bid-ask bounce is the shift of individual stock prices from the ask to the bid if a sell order follows a buy order and vice versa. Bid-ask bounce is artifact of the process by which liquidity demands are routinely satisfied. Although, in fact, only the realization of earlier volatility are related with program trading, volatility and program trades artificially seem to have a relationship since a program trade refreshes many stale prices together so that the index realizes its underlying value.

Grossman (1988b) argues that introduction of derivative markets increases the use of program trading strategies to exercise spot/futures arbitrage, market timing, and portfolio insurance. Option markets simplify the forecasting of price volatility and provide information about the cost of insurance strategies, thus stock volatility problem may decrease in case of no regulations, such as excessive capital and margin requirements, reducing the effectiveness of these markets. Moreover, trading real put options maintain the transmission of information to market participants about the futures price volatility related with dynamic hedging strategies. Potential liquidity providers have more information, which enables the absorption of trades implied by the dynamic hedging strategies and decrease of future stock price volatility.

Grossman (1988a) conducts a study on the significant relationship between program trading and NYSE for the period January 1987 to October 1987. No significant evidence about the existence of the relationship is found though some of the high volatility days expose high program trading. However, the results indicate the existence of a statistically significant positive relationship between non-program trading intensity and volatility.

Harris, Sofiano and Shapiro (1994) examine the effect of program trading on S&P 500 index volatility covering the period 1989 to 1990. They find a significant relationship between program trading and intraday price changes which may be due to bid-ask bounce, updating stale prices caused by program trades, and initiation of program trades in response to new information. However, no evidence is found in favor of the hypothesis that program trades cause excess volatility. Moreover, they reveal that program trades do not cause major short term liquidity problems.

Hogan, Kroner and Sultan (1997) investigate the correlation between program trading, non-program trading, and market volatility through estimating the joint distribution of spot and futures market returns via multivariate GARCH method. They find weak correlation between non-program trading and volatility which indicates a significant relationship between program trading and volatility, causing the strong correlation between aggregate market volume and volatility. They also prove that the positive relationship between program trading volume and volatility is stronger than that of the one between non-program trading and volatility. Moreover, Sell-program trades are associated with higher market volatility than buy-program trades. They also provide evidence that the effect of program trading on futures market volatility and on cash market volatility is the same.

Grossman (1988b) states that using program trades in systematic attempts to lock in capital gains is called portfolio insurance. He argues that market participants implementing portfolio insurance strategies only indirect information flow about insurance into market, thus portfolio insurers can violate the market through organized selling. Also distorted information flow about the volume of insurance decreases the futures price volatility. Program trading being a simple version of stop-loss trading strategies is based on selling security after a price fall in an attempt to fix in previously acquired capital gains or to minimize losses. Portfolio insurance strategies involve conveying funds to the risky asset when the value of the risky asset increases, and shifting away from the risky assets as their value decreases. Hence, portfolio insurance strategies increase stock market volatility although portfolio insurance hedges investors against a common (market) risk. Leland (1980) argues that portfolio insurance strategy is preferred by investors who have average expectations, but whose risk tolerance increases with wealth more rapidly than average, or who have average risk tolerance, but whose expectations of returns are more optimistic than average.

Also Blake (1996) examines the financial asset portfolios of interest-bearing accounts bonds and shares held by investors in the UK for the period 1946 to 1991 and finds that investors are willing to pay for portfolio insurance and willing to hold risky assets unless they are compensated with a sufficiently high risk premium. Donaldson and Uhlig (1993) generate a model portfolio insurance and asset price model to test the relationship between portfolio insurance and asset prices. They find a negative relationship between portfolio insurance activity and stock market volatility.

Basak (1995) examines the impact of portfolio insurance on market and asset price dynamics. Contrary to common criticism, he proves that portfolio insurance strategy decreases stock market volatility and risk premium, which indicates portfolio insurers are risk averse than normal agents and buys more synthetic put options consisting of a long position in a bond and a short position in a risky asset. Hence, with portfolio insurers present, to clear the markets, the risky securities must become more favorable. Basak (2002) conducts a study on portfolio insurance under a variety of modeling strategies, namely constant proportion portfolio insurance and portfolio insurance based on the synthetic put approach. In accordance with Basak (1995), it is proven that the market volatility and risk premium are decreased by the presence of portfolio insurance.

Jacklin, Kleidon and Pfleiderer (1992) investigate whether the portfolio insurance strategy is the force behind the market crash of October 1987, and find that although introduction of portfolio insurance strategy decreases volatility, the lack of information about the extend of the portfolio insurance can cause problems in market. Pain and Rand (2008) evaluate the recent developments in portfolio insurance. Contrast to critics that portfolio insurance strategy worsened the stock market crash in October 1987, and was related to the collapse of Long Term Capital Management (LTCM) in 1998, they argue that it is not likely to play significant role about financial market volatility which began in summer 2007. They also state that portfolio insurance strategy destabilizes the market volatility through three factors: market illiquidity, imperfect information and gap risk denoting the risk that the value of the investment drops sharply without trades taking place, and limited hedging instruments. The characteristic of illiquid financial markets, that small changes in demand relative to supply prompt large changes in the price, triggers more hedging flows. However, the inability to disinvest quickly makes it more difficult to hedge securities; hence volatility rises relative to liquid markets. Since dynamic hedging strategies are indiscernible for other investors and these strategies decrease the information available from market prices, these investors may misinterpret these activities as related to fundamental factors.

1.5.3. Insider Trading and Volatility

Finance literature focuses on the impact of insider trading on market volatility. Du and Wei (2004) exert a comprehensive analysis on insider trading and cross-country differences in stock market volatility. They state that insider trading denotes financial instrument trading via non-public information effecting price of an instrument. Volatility is mainly affected by the volatility of the underlying fundamentals and the maturity of the asset market, in which average experience and skill of the investors are positively related. Most importantly, they prove that clearly, more insider trading is associated with a higher market volatility. In sum, they state that the impact of insider trading is more effectual than that of other fundamental factors.

According to the theories in favor of insider trading, signal-to-noise ratio increased by insider trading stabilizes the market volatility. Another theory indicates that insider trading leading temporally volatility destabilization at the time of the price adjustment improves long-run efficiency. However, exponents argue that insider trading decrease stock market volatility and worsen economic efficiency. Due to significant shifts in price level leading to inside information to be more valuable, insiders attempt to increase volatility through choosing riskier projects or manipulating the content and the timing of the information flow. Due to the differences in regulations and, in scope of prohibited behavior, variations in penalties, and chance in the vigor with which a country chooses to enforce the laws, the volume and effect of insider trading differ across countries.

Bettis, Bizjak and Lemmon (1999) investigate the insider trading strategies consisting zero-cost collars and equity swap transactions for the period January 1996 through December 1998. They manifest that high ranking insiders, namely the CEO/Chairman of the Board, corporate officers consisting officers serving on the board of directors, and board members mostly employ these transactions. Also they evidence the volatility of stock returns is exacerbated in the following period of the purchase of these securities.

1.5.4. News Releases and Volatility

A group of studies focus on the interrelated impact of news releases and macroeconomic announcements on financial market volatility of an economy and other economies' volatility.

Darrat, Zhoung and Cheng (2007) investigate the relationship between intraday trading volume and return volatility and news impact on large and small NYSE stocks. They find that public news destabilizes volatility. However trading volume is higher when there is no information releases. They indicate that until public news arrives, overconfident investors employ aggressive trading strategies due to overestimation of the accuracy of their private news signals in the absence of public news, and after the public news flow, biased self-attribution of investors causes excessive return volatility.

Nikkinen *et al* (2006) examine the reactions of global stock markets, such as the G7 countries, the European countries other than the G7 countries, developed Asian countries, emerging Asian countries, Latin American countries and countries from transition economies, to the US macroeconomic news announcements for the period between July 1995 and March 2002. They prove that the G7 countries, European countries other than the G7 countries, developed Asian countries and emerging Asian countries are highly affected by the US macroeconomic news, which indicates the high integration with the other stock markets. However, US macroeconomic news has no significant effect on Latin America and Transition economies.

Chen *et al* (2005) assess the relationship between the France, Germany, Japan, Switzerland, UK, and US stock returns and both their own domestic news and the US information for the period January 1989 to January 2004 via linear and nonlinear models. They indicate that US news announcements, especially bad news, destabilize investigated stock markets than their own domestic news. Moreover, US market plays a more crucial role in explaining the domestic stock returns. Bad news from both domestic and US markets generates significantly more volatility, which indicates the asymmetric response of each stock market to the interactive information from domestic and US markets. Furthermore, the persistence of stock return volatility is much lower following good news from either domestic or international markets.

Hayo and Kutan (2005) examine the possible response of Indonesia, South Korea, Argentina, Brazil, Pakistan, and Russia stock markets to the International Monetary Fund (hereafter IMF) news over the period from July 1997 to December 1999. Although it is evidenced that positive IMF news increases daily stock returns by about one percentage point and vice versa, they fail to accept the hypothesis that IMF news does not have a significant impact on the volatility of the financial markets.

Blasco *et al* (2005) conduct a study on determining information type effects on close-to-open returns, open-to-close returns, volatility and volume in actively traded individual securities on the Spanish stock market during January 1997 and March 1999. They suggest that the Spanish financial market is highly affected by both bad news and the Dow Jones.

Wang and Firth (2003) examine the return and volatility spillover effects between Greater China's four emerging stock markets as well as Tokyo, London, and New York stock markets for the period 1994 to 2001 via nonlinear volatility models. They find news asymmetry in Hong Kong, Japan, the UK, and the US markets. Whereas Shanghai and Shenzhen are affected the most by the Japanese market, while the US and the UK markets influence Hong Kong and Taiwan. They evidence in favor of uni-directional returns spillovers from the advanced major international markets to the emerging Chinese markets, and bi-directional volatility spillover effect. Thus, there is volatility spillover effect among Greater China's four stock markets, and these markets are subject to volatility spillover effect from one or two of the three international stock markets, namely Japan, the UK, the and the US.

Chen, Chiang and So (2003) examine the asymmetric reaction of financial markets in a diverse group of six emerging markets, such as France, Germany, the UK, Japan, Switzerland, Canada, to a set of US news for the period from January 1985 to November 2001 via asymmetric volatility models. They find that US news announcements lead asymmetric transmission effect. Moreover, negative US news destabilizes the financial markets more than positive news.

Nikkinen and Salström (2004) examine the hypothesis that both domestic and US macroeconomic news releases significantly affect German and Finnish stock markets representing European markets. They conclude that German stock market is significantly affected by the US inflation measure of CPI and PPI whereas Finnish stock market is influenced by the PPI. US reports generate a greater effect on the Finnish stock market than on the German market due to high foreign ownership and dependence on demand from foreign countries in Finland. Moreover, US employment report and the Federal Open Market Committee meeting days destabilize both markets while domestic news releases do not.

Bomfim (2003) conducts a study on whether there is any evidence of news and pre-announcement impacts in the US market for the period 1989 to 1998 through GARCH model. Significant pre-announcement effect on volatility is found in the US market, which justifies calm-before-the storm effect indicating the volatility which is lower in the days leading up to releases of major economic data and higher on the day of the announcement itself.

Hanousek, Kocenda and Kutan (2008) evaluate the impact of macroeconomic news on the intraday volatility of Budapest, Prague, and Warsaw stock exchanges for the period 2003 through 2006. They find no significant intraday impact of their own local announcements on these markets. However, they evidence that the composite index returns volatility of the European Union (hereafter EU), the US, and neighboring markets transmit their volatility to these three new EU stock markets. Czech stock index receives volatility spillovers form Budapest and Warsaw stock exchanges as well as the US, the EU and Germany. Also EU, Germany, Prague, and Warsaw spill their volatility over the Hungary stock market. The Polish market is marginally impacted by EU news. While both Prague and Germany have a moderate spillover impact, Budapest has weak volatility transmission impact on the Poland stock market.

1.5.5 Spillover Effects and Volatility

The volatility transmissions across stock markets become popular research area in recent years. Baur and Jung (2006) examine the spillover effects around the opening time between DJIA and Deutsche Aktienindex (hereafter DAX) daily returns covering the period 2 January 1998 through 29 December 2000 by using aggregate-shock model (hereafter AS). They prove the influence of foreign daytime returns on the domestic overnight returns while no spillover effect of previous daytime returns is found. However DAX have short-lived spillover effect on DJIA in noon-to-3:30 pm (CET) segment.

Lee and Rui and Wang (2004) investigate whether returns and volatility spillovers from NASDAQ and domestic market is an important source of volatility in second board markets of Singapore, Japan, Taiwan, and South Korea via EGARCH model. They find strong spillover effects and argue that local main board markets transmit volatility to the corresponding second board markets.

Egert and Kocenda (2007) exert a research on spillover effects of Eastern and Western European Countries and interactions with Frankfurt, London and Paris stock exchanges using intraday data covering the period June 2003 to February 2005 through component GARCH (hereafter CGARCH) model. They prove volatility spillover effects among the Central and Eastern Europe (hereafter CEE) markets, among the Western markets and from Western markets to CEE markets, but also from both Budapest Stock Exchange and Warsaw Stock Exchange to German Stock exchange and Russian Stock Exchange, respectively. Also spillover effects from returns to returns among the CEE markets, among the Western markets and from Western Europe to CEE are found.

Ane and Labidi (2006) assess interdependence among the UK, France and Germany stock markets returns from January 1990 to December 2001 via bivariate asymmetric models. They find significant evidence in favor of mean spillovers from the French and the UK stock markets to the German stock market, and bivariate spillovers among the French and German markets, as well as a volatility transmission from the German to the British market.

Billio and Pelizzon (2003) investigate volatility spillover from the world index to European stock markets of Germany, France, Italy, Spain, and the UK and the impact of deregulation, globalization, recent financial crises, the convergence of European economies and the introduction of the euro on spillover effects using regime-switching models. They find significant spillover effect from world index to Germany and Spain, and spillover from both world index and Germany to French, the UK. They indicate that macroeconomic factors play important role as determinants of volatility.

1.5.6. Macroeconomic Factors and Volatility

A number of studies focus on the effect of macroeconomic factors of stock market volatility. Du and Wei (2004) cite that volatility in financial market is positively related with volatility in gross domestic product (GDP) in an economy. Also they evidence that more volatile corporate operating income stream is associated with a more volatile aggregate stock return due to motivation of insider traders to invest in riskier projects. Moreover, stock market volatility is destabilized in proportion to the concentration of wealth and polarized income distribution. Volatility in macroeconomic factors, such as exchange rate and inflation, increases the volatility in stock markets. Also predictability of monetary policy and openness of trade regimes are negatively associated to financial market volatility. Furthermore, they manifest the existence of inverse proportion between volatility and both maturity and liquidity. They find weak evidence supporting the law enforcement on insider stabilizes stock market volatility.

Errunza and Hogan (1998) make an attempt to identify the determinants of volatility in the European stock markets of Italy, UK, France, Germany, Switzerland, Netherlands, Belgium, and USA covering the period January 1959 to March 1993. They indicate that macroeconomic factors of inflation, productivity growth rate and money supply growth rate are not the force behind the stock market volatility of US, UK, Switzerland, and Belgium. However, lagged money supply growth affects Germany and France. Furthermore, it is evidenced that real economic uncertainty, rather than monetary uncertainty, exacerbates volatility in Italy and Netherlands. Industrial production also affects Italy and Netherlands.

Hassan and Francis (1998) assess the impact of macroeconomic factors, namely dividend yield, the default spread, the term structure on stock market volatility of US. They find reciprocal volatility spillover impact of large and small firm returns. Moreover, dividend yield, the default spread, the term structure influence both small and large firm return conditional volatilities, but not lagged volatility.

Leblang and Mukherjee (2005) point out an important factor destabilizing volatility and examine the reaction of financial market to government partisanship and traders' expectations of electoral victory by the right-wing or left-wing party for 15 U.S. Presidential election years denoting the period between 1930 and 2000. They find that when traders expect the left-wing party to win elections or during the incumbency of left-wing governments, the mean and volatility of stock prices decrease due to decrease in trading volume resulting from rational expectations of higher inflation under left-wing administrations. Opposite situation is valid for right-wing administrations. Hayford and Malliaris (2004) assess the influence of Federal Reserve System (hereafter FED) policy on stock market valuations during the period and find that FED leads high valuations of the stock market during this period.

Patro and Wald and Wu (2002) investigate the predictability of the volatilities of the 16 Organisation for Economic Co-operation and Development (hereaftet OECD) countries in terms of macroeconomic and financial variables by employing time-varying two-factor international asset pricing model for the period covering January 1980 to December 1979. The results indicate that factors of import, export, inflation, tax, government surplus, term spread, market capitalization, dividend yield, and price-to-book ratio have significant impact on economies' world market risk exposure, which indicates the importance of these variables on portfolio selection decision and policy making. World market risk has positive relation with export, inflation, taxes to GDP ratio, market capitalization to total world capitalization ratio, and negative relation with import, government surplus to GDP ratio, credit rating, dividend yield, term spread.

Bekaert and Harvey (1996) extensively investigate the factors making the volatility to vary across emerging market, especially concerning the timing of capital market reforms. They use semi parametric ARCH (SPARCH), linear and nonlinear versions of the Factor Model. They find that the factors of asset concentration, stock market development/ economic integration, microstructure effect, and macroeconomic influences and political risks lead volatility to differ between developed and emerging markets. Moreover, they conclude that although in fully integrated markets, world factors influence the volatility, in segmented capital markets volatility is more likely to be influenced by local factors. Volatility level decreases in an economy open to world trade or experiencing liberalization

1.6. Volatility Studies on Istanbul Stock Exchange

A number of studies have been focusing on volatility in ISE, which is one of the most appealing developing stock market. ISE has the tenth fast growing domestic market capitalization in 2007. Also performance of broad market indices increases around 42%, leading the ISE to be the tenth best performing exchange among World Federation of Exchanges (hereafter WFE) members and fifth best performing exchange in Europe region.

Turkey is one of the leading emerging markets. Turkey was integrated with the world capital markets via the establishment of the ISE in late 1985. ISE was the fifth largest exchange by total value of bonds traded about USD 405 billion in 2006. Turkey had the GDP of 402.71 billion US dollar with the growth rate of 6.10% in 2006. Market capitalization of the Turkey stock market was around 162 billion US dollar denoting 40% of the GDP in 2006. The domestic market capitalization increased 172% since 1986. The number of listed companies reached 316 in ISE with the increase of 295% since 1986. Moreover, the 15 newly listed companies contributed about 4.1 million US dollar to the market capitalization in 2006. Investment inflow via initial and secondary public offerings reached 861.5 million US dollar in 2006 (World Federation of Exchanges).

Turkey’s capital account liberalization in 1989 opened stock market to foreign investors through no restrictions on trading and repatriation of capital and profits, along with fully convertible currency policy, made ISE not only an attractive investment alternative, but also sensitive to capital movements and shocks resulting from news on macroeconomic data, global crises, and economic and political developments in Turkey. Due to convenient investment environment, the share of foreign investors in ISE reached the 70% in 2007. However, the ISE volatility increased significantly after the liberalization in 1989. In recent history, financial crises Turkey faced in 1994, 1997, 1998, 2000 and 2001 had devastating influences on ISE. Hence, modeling and studying volatility of ISE is critical for global investors in terms of portfolio diversification and other risk management strategies.

Bildik and Gülay (2008) examine whether changes in value weighted index composition in ISE is a determinant of stock price and volume. They observe the price and volume increase in both included stocks in index and excluded stocks from index in the pre-announcement period whereas the price and volume decrease (increase) occurs for the excluded (included) stocks from (in) index on announcement days. They also indicate that the existence of volatility shift in the excluded stocks on announcement day may stem from margin trading, lending and borrowing and short selling. In sum, change in index composition significantly effect stock price, trading volume and volatility.

Also Bildik and Gülay (2006) investigate the impact of price limits on volatility. They find that price limits have a significant effect on the stock market. Bildik (2001) represents a study on intraday price behavior of ISE for the period 1996 to 1999. He evidence the W-shape pattern in stock prices, volume, and volatility, which denotes the existence of increasing trend at the beginning of the day and upward movement at the end of the trading day. Also he proves the large and positive return at the opening and closing of each trading day of the week, and positive mean returns during the opening hour of Mondays. Furthermore, he finds that volatility is higher at the openings and follows an L-shape pattern during the both sessions. Intraday volatility increases for the first minute after the opening both in the morning and the afternoon sessions, and then decreases. The volatility reduces almost to the lowest level of the day at day-end in each weekday. The closing volatility is lower than both the morning and afternoon opening volatility.

Huang and Yang (2000) evaluate the reaction of the stock price volatility to financial liberalization process in emerging markets. They evidence the exacerbated volatility shifts after market liberalization. Alper and Yılmaz (2004) investigate volatility transmission from the financial centers, consisting the US, the UK, Hong Kong, Brazil, Korea, and Russia to ISE. They state that as soon as the Asian crisis spreads out to South Korea and Hong Kong, significant volatility spillover occurs to ISE.

Darrat and Benkato (2003) research the degree of financial integration of ISE to the US, Japan, and the Europe markets and the impact of financial liberalization process on financial integration. They state that volatility spillover increases uncertainty and non-systematic risk of foreign portfolio, which causes a decrease in the confidence to the financial market. Volatility spillover from the US and the UK to Turkey is found after market liberalization, but not before liberalization. The results suggest that financial liberalization process stabilizes the volatility in ISE. Moreover, volatility spillover effect caused by financial liberalization improves financial globalization and stability in Turkey stock market.

Girard and Biswas (2007) represent a comprehensive study on the interaction between volume and volatility in world financial markets including Turkey. They state that developed markets are less sensitive to shocks and unexpected volume. Also emerging markets exhibit strong positive relationship between volatility and volume, which suggests high bid-ask spreads, speculative transactions done by informed traders, and market illiquidity.

1.7. Efficient Market Hypothesis and Long Memory in Return and Volatility

Fama (1970) states that investors, all of whom are rational, implement arbitrage quickly in case the existence of deviation in price changes in an efficient market. Thus it is impossible to gain abnormal returns. Three types of market efficiency are defined: weak form efficiency, semi-strong efficiency, and strong form efficiency. The weak form of the efficient market hypothesis suggests that past prices are not determinants of the futures prices. The semi strong form of the efficient market hypothesis claims that the prices impound the all publicly available information. Finally, the strong form of the efficient market hypothesis asserts that stock prices reflect all information, not only all public information.

In a weak form efficient market, past prices can not be determinants of futures prices due to fully reflection of information occurring in the past. Hence, price series follow random walk process. Making profits over market returns, or generating speculative gains are impossible. Thus, efficient market hypothesis assume that series of price have no memory, which means that past and future prices are independent. Since the long memory of a series can be defined as dependence among distance prices, series with long memory pattern putrefies the weak form efficiency. Hence long memory of returns estimated by ARFIMA model contradicts the weak form market efficiency. Fama (1970) states that new information flow is quickly reflected in prices changes in an efficient market. Thus, the changes in price absorb the impact of news rapidly, which denotes that there is no dependence between distance price changes. Thus, dependence in price changes, so long memory in volatility, putrefies the weak form market efficiency indirectly through spoiling the pricing mechanism.

Henry (2002) conducts a study on searching long range dependence in monthly stock markets containing the US, Japan, Germany, the UK, Hong Kong, Taiwan, South Korea, Singapore, and Australia by using parametric and semi parametric estimators. He finds out strong evidence of long memory in the South Korea and some evidence of long range dependence in German, Nikkei 225 Japan, and Taiwan stock markets.

Limam (2003) exerts effort to analyze the long memory of developed stock market index returns of Tokyo, the UK, the US and emerging stock market index returns of Brazil, India, Mexico, as well as those of eight Arab stock market index returns of Bahrain, Egypt, Amman, Kuwait, Morocco, Oman, Saudi Arabia, and Tunis to investigate the link between fractional integration dynamics in stock returns and the level of stock market development. using parametric and semi parametric estimation procedures of Geweke-Porter-Hudak (1983) (hereafter GPH) modified rescaled range statistic (hereafter R/S) suggested by Lo (1991), he finds out that while developed markets have short memory as well as emerging markets of Brazil, India, and Mexico, Arab countries, except Jordan, have long memory indicating that long memory is related with the thinner markets of the sample. Overall, he concludes that fractional integration dynamics in stock returns is strongly linked to the level of development in stock markets, the peculiar characteristics, and environment of each stock market.

Bhardwaj and Swanson (2006) evaluate forecasting performance of ARFIMA models along with AR, MA, ARMA, GARCH, and related models, based on mean square forecast errors (MSFEs) and Diebold and Mariano(1995) and Clark and McCracken (2001) predictive accuracy tests. Estimating long memory characteristic of S&P 500 daily stock returns covering from 4 January 1928 to September 30, 2003 and other 4 major stock index returns of UK, Germany, and Japan stock markets covering from 4 January 1981 to 18 January 2002 via estimation methods of GPH, Whittle (hereafter WHI), Rescaled Range (hereafter RR), Approximate Maximum Likelihood (hereafter AML), and ARFIMA, they find the evidence of existence of long memory and that ARFIMA models give better forecast accuracy than linear models. Additionally, they provide further support for their findings via examination of the Stock and Watson's (2002) large (215 variable) dataset.

Tolvi (2003a) uses GPH and Lagrange Multiplier (LM) estimation methods to analyze the presence of Long memory in six daily Finnish Stock market returns. Evidence of long memory is found in 24% to 67% of the series depending on estimation method. Based on GPH estimation results, indices have long memory property. Additionally, Tolvi (2003b) investigates long-range dependence and effect of outliers on long memory property in the monthly stock returns of 16 OECD countries including Australia, Germany, Belgium, Canada, Denmark, Spain, Finland, France, Ireland, Italy, Japan, The Netherlands, Norway, Sweden, UK, and daily stock market index of US via ARFIMA models. He finds long-range dependence in Denmark, Finland and Ireland; however, in case of taking outliers into account, only Ireland stock market has long memory in the outlier model.

Wright (1999) exerts an effort to examine the possibility of long memory in a number of emerging market stock returns including Argentina, Brazil, Chile, Colombia, Greece, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Taiwan, Thailand, Venezuella, and Zimbabwe by means of log-periodogram regression, and finds a positive long memory in seven of the seventeen financial series of Chile, Philippines, Thailand, Columbia, Korea, Malaysia, and Greek. Thus, very little evidence has been found for long memory in stock returns of emerging markets.

Byers and Peel (2001) investigate the long memory in high/low prices of a number of assets including S&P 500 futures price, FT 30 index, and gold prices, as well as inter-war exchange rates sterling against the US dollar, the Belgian franc, the French franc, the lira, and post-war exchange rates sterling against the US dollar, yen, the Deutschemark, the French franc, the lira. They get supportive evidence of existing long-range dependence by means of using R/S statictics, ARFIMA models, and GPH method.

Christensen and Nielsen (2005) conduct a study on determining long memory behaviors in monthly realized volatility obtained from returns on S&P stock market index covering the period 1 January 1988 to 31 December 2002 and VIX implied volatility series from the CBOE covering the period January 1990 to December 2005 via univariate ARFIMA and bivariate VARMA models. They prove significant evidence of presence of long memory in both realized and implied volatility.

Blasco and Santamaria (1996) use the modified rescaled range (hereafter MMR) test and the GPH test to detect the presence of long memory in the weighted Madrid Stock Exchange. The result of the investigation indicates that while financial data exhibits strong memory patterns, such dependence is not exhibited over extremely long time spans.

ARFIMA models are used for modeling return series since ARFIMA models capture long memory in returns in recent years. Barkoulas and Baum (1997) investigate fractional dynamic behavior of spot and forward exchange rates of the Japanese yen vis-à-vis stock prices, major currencies, currency forward premia, and rates for 3- and 6- month Euroyen deposits and the corresponding term premium series by analyzing long memory parameter estimated via the spectral regression and Gaussian semi parametric methods. This study reveals the evidence of long-range dependence in the forward premia series, the Euroyen deposit rates, and their term premium.

Barkoulas, Baum, and Travlos (1996) employ the spectral regression method to test for stochastic long memory in Athens Stock Exchange weekly returns spanning 7 January 1981 to 27 December 1990 as an emerging market and provide significant and robust evidence of positive long-term persistence in Greek stock market contrary to the findings for major capital markets. However, using ARFIMA-GARCH model estimated by conditional maximum likelihood method to test fractional integration of Athens Stock Exchange weekly returns spanning same as Barkoulas *et al* (1996), Vougas (2004) finds very little evidence in favor of fractional integration. Dockery and Vergary (2001) investigate long range dependence in the 72 stocks of Athens Stock Exchange individually by applying Robinson's LM test and find fractional differencing for only 6 stocks, one of which suggests long-run mean reversion. Panas (2001) exerts Hurst exponent and ARFIMA models to determine long memory in the sample of 17 stocks of Athens Stock Exchange using daily data, and provides the evidence of existence of long-memory.

Resende and Teixeria (2002) research the existence of long-range dependence in The São Paulo Stock Market weekly return, which is spanning from 1 October 1986 to 31 December 1999. They divide the period into two sub-periods before and after the Real Stabilization Plan and find evidence contrary to long memory indicating the short memory for both periods despite the so-called reforms the Brazilian economy underwent in the 1990s and , especially, after the Real Plan via ARFIMA models.

Berg and Lyhagen (1998) investigate the memory patterns of monthly stock returns of Stockholm Stock Exchange covering 1919 to 1995 and, weekly and daily data for the 1980s and first part of the 1990s by employing the modified rescaled range (R/S) test, ARFIMA models and GPH1983 methods. Although GPH method provides significant results for nominal and real monthly stock returns for the full and the first half of the sample at the two frequencies used in the spectral analysis indicating that the Stockholm Stock Exchange displayed long memory in the first half of this century, R/S test and ARFIMA models tests provide no support for long memory.

Besides more efficient forecasting and modeling results, ARFIMA models evaluate the weak form efficiency since long memory denotes the predictability of future returns through part returns. There is a vast literature evaluating weak form market efficiency via ARFIMA and other models.

Antoniou and Ergul and Holmes (1997) investigate the effects of thin trading and non – linear behavior leading the market inefficiency in Istanbul Stock Exchange for the period from 1983 to 1993 via the models of random walk and GARCH-M. They indicate that although thin trading, non – linear behavior and market inefficiency are the best characteristics of the market up to 1990, the efficiency of the market was improved due to increasing trading volume, reliable information flows, educated investors and suitable institutional framework caused by the adjustments of the regulatory structure from 1989.

Balaban (1995a) conduct a study on analyzing informational efficiency in Istanbul Stock Exchange for the period January 1988 to August 1994. The results of the random walk model for weak form efficiency suggest that the market is not weak form efficient. Additionally, he investigates day of the week effects to test semi strong efficiency and concludes that daily anomalies lead market not semi-strong efficient. Moreover, Balaban (1995b) examines the empiric features of Istanbul Stock Exchange by parametric and non parametric testing of random walk hypothesis on various frequencies of composite index returns. He evidenced that daily and weekly returns follow random walk although monthly returns do not. Moreover, he finds a significant evidence of day of the week effect changing in direction and magnitude across years and month of the year effect for the period 1986 – 1994. Thus, He suggests that the ISE is neither weak-form nor semi-strong-form efficient in case of using daily and weekly data. Nevertheless, his consequences about market efficiency is contrary to Alparslan's (1989) study on testing weak form efficiency of the Istanbul Stock Exchange first common stock market's adjusted-price data covering the period from January 10, 1986, to October 28, 1988. He states that statistical tests of independence (autocorrelation and runs tests) suggest the weak form efficiency. Balaban (1995c) conducts a study on detecting month of the year effects in Istanbul Stock Exchange between 1981 and 1993. The results that significantly large returns during January, June and September, that could be reason of asymmetric information among traders, indicate the calendar anomalies and provide evidence against Efficient Market Hypothesis.

Balaban and Kunter (1996) investigate semi – strong form of informal efficiency in stock market, foreign exchange market and interbank money market with the help of Granger-causality tests in Turkey. Results could not provide enough evidence to prove in favor of market efficiency with respect to daily changes of market liquidity in three markets. Balaban, Candemir and Kunter (1996) evaluate informal efficiency of the Istanbul Stock Exchange with respect to high frequency observations of some monetary variables to eliminate the loss of information generating from aggregation of data. Results of structural models indicate that market inefficiency consistent with the previous research findings.

Aydoğan and Muradoğlu (1998) test the market efficiency with respect to announcement and implementation of rights issues and stock dividends in the Istanbul Stock Exchange by means of event study methodology and non-parametric tests. They indicate that the effect of the board meeting or the actual implementation of stock dividends - rights offerings on price reactions is inversely proportional to market maturity.

Buguk and Brorsen (2003) exert a detailed research of informational efficiency in Istanbul Stock Exchange by applying more robust statistical techniques including a number of random walk tests accompanied by LOMAC single variance ratio test, rank- and sign-based variance ratio tests, GPH test, and the augmented Dickey–Fuller (hereafter ADF) test to the weekly closing price of the composite, financial, and industrial indexes for the period of 1992–1999. The ADF unit root, LOMAC variance ratio, and GPH fractional integration tests provide significant evidence in favor of random walk implying the market efficiency; however non parametric rank- and sign-based variance ratio tests results indicate the indices do not follow a random walk.

Bildik and Gülay (2002) analyze the weak form efficiency of the Istanbul Stock Exchange via investigating profitability of a number of contrarian strategies, which is buying past losers and selling past winners realize significant abnormal profits to the investors, based on past prices of stocks from January 1991 to December 2000. The results of the study suggest the existence of contrarian strategies. They find that the future returns and reversals in prices can be predictable by past return, indicating market inefficiency in Istanbul Stock Exchange.

Balaban (1994) examines the day-of-the week effect in Istanbul securities exchange composite index return data for the period January 4, 1988 and August, 5 1994 via sign analysis and finds the significant, but varying in direction and magnitude through time, day of the week effects putrefying the Efficient Market Hypothesis.

Bildik (2004) attempts to detect calendar anomalies of such as the day-of-the week, turn-of-the-year and January, turn-of-the-month, intra-month, and holiday effects violating the weak form market efficiency in stock returns as well as in trading volume in ISE. He finds, in accordance with the international evidence, that both ISE returns and trading volume are affected by the calendar anomalies. Additionally, results suggest that the combination of various factors such as settlement procedures, window-dressing, information processing, inventory adjustments, risk, standardization in payment systems, regularities in dividend payments and earnings announcements, market closures, and measurement errors may effect the most of the anomalies. However, he could not find enough evidence to prove that public authorities, regulators of markets, and institutional practices have an important productive impact on the existence of the seasonalities in stock markets.

Dicle and Hassan (2006) employ GARCH model to investigate trading session-of-the week effect in thirty-one different indices traded in Istanbul Stock Exchange. They discover the significant session-of-the week effect changing for different years. Moreover, they find the evidences of negative morning returns on Mondays and positive afternoon returns on Fridays in favor of the weekend uncertainty explanation for the day of-the-week effect. Finally, they conclude that session-of-the-week effect is economically significant due to the existence of significant and continued profits of trading rules for session of the week effect. Dicle and Hassan (2007) also examine the day of the week effect by using GARCH model to all indices of ISE for the period from the 1987 to 2005. The statistically significant day of the week effect for Mondays (with negative returns), for Thursdays (with positive returns) and for Fridays (with positive returns) is proven based on results. Generally, studies on market efficiency through employing.

Müslümov, Aras and Kurtuluş (2003) examine the weak form efficiency by applying the GARCH-M and random walk models to ISE100 index and individual stocks constituting of the index for the 13 June 1991 through 29 November 2001 time period. They indicate that approximately %45 of the individual stocks exhibit a random walk pattern. Moreover, from the two equal parts of the ISE-100 index, the first period of the index do not follow a random walk due to the existence of a significant autoregressive term in the return series. Finally, they find evidence in favor of the Efficient Market Hypothesis due to the random walk pattern in the second part of the index. We investigate the existence of weak form market efficiency via ARFIMA models. General findings of studies employing ARFIMA models indicate that emerging markets putrefies the weak form of efficient market hypothesis. The econometric explanations of ARFIMA model are presented in Appendix A.

CHAPTER II

LONG AND SHORT MEMORY MODELS

In this chapter, long memory and short memory in volatility model types are explained. Also a detailed literature on memory models is discussed. The econometric explanations of both long and short memory in volatility models are presented in Appendix B.

2.1. Models of Long Memory in Volatility

Volatility models can be classified into two groups, namely short memory and long memory models, in terms of memory pattern of volatility in a given time series. Most popular long memory models are FIGARCH and fractionally integrated EGARCH (hereafter FIEGARCH). Since most of the financial series exhibit autocorrelation in squared returns, it is likely that long memory models more efficient estimation results than short memory models.

Wang and Hsu (2006) asses the effectiveness of alternative volatility models including EGARCH, FIEGARCH, EGARCH-jump and EGARCH- skewed-t models based upon a generalized EGARCH model with the time series of stock market indices of the G8 countries (the US, Japan, the UK, Germany, France, Canada, Italy and Spain) covering the period from July 1990 to June 2005. Based on the EGARCH model, they find two conventional stylized facts of volatility clustering and news impact asymmetry. Moreover, FIEGARCH estimation results provide significant evidence of the relatively good performance with regard to US stock market returns only, this suggests that the long-memory pattern captured by the fractionally-integrated volatility model may not be a globally stylized fact.

Bollerslev and Mikkelsen (1999) use EGARCH, IEGARCH, and FIEGARCH models to model daily and weekly S&P 500 returns from 24 March 1961 to 18 January 1991, and CBOE traded S&P500 put long-term equity anticipation securities (hereafter LEAPS) from 21 January 1991 to 30 September 1993 and they find that long-run dynamics in the S&P 500 volatility process is best characterized by a fractionally integrated time series model outperforming EGARCH and IEGARCH proved by simulated option prices.

Brandt and Jones (2006) conduct a research on analyzing forecasting performance of EGARCH based models of FIEGARCH, variants of REGARCH, FIREGARCH by using daily S&P 500 index data for 1983–2004. They find long-range dependence based on fractionally integrated models in accordance with previous researches.

Maheu (2002) exerts a study on modeling daily returns from the three equity indices of New York Stock Exchange (NYSE) composite index from January 1966 to August 2001, S&P 500 composite index from January 1928 to June 2001, and DJIA from October 1928 to January 2000 with the help of GARCH(1,1), CGARCH, and FIGARCH models and finds strong evidence in favor of the presence of long-range dependence for three indices. Long memory property should be taken into account in risk management.

Eric (2004) analyze short correlation structure in four series of S&P 500 index, Dow Jones Industrial Average, as well as the CRSP equally weighted index and the CRSP value weighted index measuring the US stock market through short and long memory GARCH type models as well as ARFIMA, GPH and wavelet analysis. He comes to conclusion that all the indices investigated have long memory.

McMillan and Speight (2006) employ FIGARCH model for determining whether returns volatility displays long-memory characteristics and HARCH model to capture the effects of market components on conditional variance based on price shocks over time intervals of different size in 30-min quotations for the S&P 500 index over the year 1 January to 31 December 1996. They find significant evidence in favor of long memory and heterogeneous components.

Gospodinov, Gavala and Jiang (2006) evaluate the forecasting performance of FIGARCH, FIEGARCH, and long memory stochastic volatility (hereafter LMSV) models, and investigate the properties of S&P 100 index for the period 1 June 1988 to 17 May 2002. The estimates from the EGARCH and FIEGARCH models reveal the existence of long memory and leverage effect. Negative shocks lead to a large increase in volatility, but positive news has almost no impact on volatility. Additionally, they find that the FIEGARCH intercept-corrected forecasts seem to be the best-performing individual forecasting method and the combination forecasts constructed by excluding the LMSV model hardly dominate them.

Kang and Yoon (2006) examine the long memory feature and the property of asymmetric volatility through ARFIMA, GARCH, IGARCH, EGARCH, and FIEGARCH in the four Asian stock markets of Japan, South Korea, Hong Kong, and Singapore covering the period from January 1990 to December 2005. Although ARFIMA models give little evidence in favor of long-range dependence, when remaining ARCH effect is allowed, the FIGARCH model beats the GARCH and IGARCH models indicating the existence of long memory in Asian stock markets. After property of asymmetry is proven via EGARCH, they analyze the property of long memory and asymmetric volatility simultaneously by means of FIEGARCH model, and conclude that there is asymmetric long memory feature in Asian stock market volatility.

Also Kang and Yoon (2007) investigate dual long memory, which is long memory occurring both in mean and in volatility simultaneously, by using ARFIMA-FIGARCH model on two daily Korean stock price indices. They find the property of long memory in volatility and in mean on both indices. Moreover, they indicate that skewed student-t distribution outperforms the student-t distribution in terms of capturing asymmetry on both indices.

Lee, Kim and Lee (2000) study the estimating long memory in the Korean stock market by way of GARCH, IGARCH, and FIGARCH. They reveal the significant evidence of long memory in Korea stock market.

Hatgioannides and Mesomeris (2007) use ARFIMA-FIGARCH model to asses the long memory in mean and in volatility on four Latin American indices of Mexico, Brazil, Argentina, and Chile, as well as four Asian indices of Philippines, Taiwan, Thailand, Indonesia returns covering the period 1 January 1988 to 31 May

2002. ARFIMA-FIGARCH test results indicate no long memory in mean, but in volatility.

Floros, Jaffry and Lima (2007) evaluate the memory characteristics of the Portuguese stock market. They analyze two sample periods covering from 4 January 1993 to 13 January 2006 as a whole period, and from 1 February 2002 to 13 January 2006, the period starting after the merger of the Portuguese Stock Exchange with Euronext by employing ARFIMA-FIGARCH models. Although they find significant evidence in favor of dual long memory in the whole period, ARFIMA-FIGARCH models indicates long memory only in volatility over the merger period, thus implying the improvement in efficiency after the merger with Euronext.

Caporin (2003) studies the identification problems in FIGARCH models whereby simulations and FIGARCH application of Italian Stock market index covering from 20 March 2000 to 15 March 2001 indicating long memory in Italian Stock Exchange.

Kılıç (2004) uses FIGARCH model to investigate the long memory property of ISE100 index returns covering the period from 4 January 1988 to 23 October 2003. The results indicate the existence of long memory in volatility and the superiority of FIGARCH over GARCH model. Thus he rejects the traditional GARCH specification for ISE100 index returns.

Cheong, Nor and Isa (2007) investigate the distribution and memory properties of standardized returns whereby employing realized volatility and GARCH and long memory models of FIGARCH and CGARCH. Using high frequency Kuala Lumpur Stock Exchange index transaction prices during the period 1 January 2003 to 15 January 2006 and S&P 500 index as a benchmark, they provide significant evidence that the realized–standardized returns follow a Gaussian distribution, and excess kurtosis can be reduced but not eliminated by means of using the standardized returns by GARCH models. Also they prove the existence of long-range dependence in Kuala Lumpur Stock Exchange index.

Ñíguez (2003) exert a study to evaluate the relative success of the Gaussian and Student-t GARCH and FIGARCH type models of Asymmetric GARCH (hereafter AGARCH), Asymmetric Power ARCH (hereafter APARCH), exponentially weighted moving average EWMA, FIGARCH, and FIAPARCH for volatility and Value-at-Risk forecasting of daily stock-returns using data from the Spanish equity index covering the period from July 1, 1987 to December 30, 2002. The research results in significant evidence of existence of long run dependence and asymmetric responses of volatility to negative and positive innovations in the Spanish equity index.

Gandhi, Saadi and Dutta (2006) examine the random walk hypothesis in the daily returns of the Tunisian Stock Exchange from 2 January 1998 to 1 April 2004 by examining both linear and non-linear dependence. The result of Brock, Dechert and Scheinkman's (1987) BDS test implemented to standardized residuals from FIEGARCH model which has successfully accounted for all the non-linearity in the returns series indicates that that the conditional heteroskedasticity is not responsible for all the nonlinearity in index returns, and there is some other hidden structure in the data. Consequently, they reject the efficient market hypothesis for Tunisian Stock Exchange General Price Index. Also, taking into account of insignificant leverage coefficient in FIEGARCH, they conclude that conditional variance of future returns responds similarly to positive and negative shocks. Finally, results of FIEGARCH and FIGARCH models provide evidence in favor of long-range dependence in Tunisian Stock Exchange.

Veiga (2006) examines the forecasting performance of a continuous time stochastic volatility model of two volatility factors (SV2F) compared with a class of alternative models (GARCH, FIGARCH, Hyperbolic GARCH (hereafter HYGARCH), FIEGARCH and CGARCH) in daily Microsoft stock return and finds significant long memory coefficient via FIGARCH. However, FIEGARCH modeling process results in long-memory at ten percent significance level.

2.2. Models of Short Memory in Volatility

The short memory models, that are the variants of GARCH model, are employed to modeling volatility and evaluating forecasting performance in many empirical researches. In this thesis, the most popular short memory models of GARCH, IGARCH, EGARCH, and GJR-GARCH models are used.

Griffin, Nardari and Shultz (2006) analyze the relation between returns and volume across markets for developed and developing markets. Also, they divide 46 countries into groups of high - income and developing markets and employ an EGARCH (1, 1) specification capturing the asymmetric relationship between returns and volatility to daily index returns and cumulate the daily estimated volatilities into weekly volatilities. According to the test of asymmetry, it is proven that larger positive return shocks lead to proportionally larger increases in volume than smaller positive return shocks. They also find that larger positive return shocks lead to proportionally larger increases in volume than smaller positive return shocks, but the picture is more complicated for negative shocks. They declare that, the decrease in trading for large negative shocks is less than that for other negative shocks on account of the left tail of the return distribution.

Harvey and Siddique (1999) run a research for jointly modeling and estimating conditional mean, variance, and conditional skewness in a maximum likelihood framework, assuming a non-central conditional t distribution by estimating GARCH and EGARCH based models on daily, weekly, and monthly stock returns of the US, German, Japanese, Mexican, Chilean, Taiwanese, and Thailand. They get significant evidence that autoregressive conditional skewness is important, moreover, that the attachment of skewness impacts the persistence in variance and can cause asymmetry in variance to disappear.

Koutmos (1999) uses Asymmetric Autoregressive Exponential GARCH (hereafter ASAR EGARCH) model on index stock returns of six emerging markets including Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand from 2 January 1986 to 1 December 1995 for determining whether index stock returns of six emerging markets adjust asymmetrically to past information. They find significant evidence that both volatilities and prices, more importantly conditional mean, respond asymmetrically to past information. Additionally, negative past returns are less persistent than positive past returns of an equal magnitude.

Bailie and DeGennaro (1990) analyze the volatility of CRSP value weighted index returns traded in from January 1, 1970, through December 22, 1987 and investigate the relationship between mean returns on a stock portfolio and its conditional variance or standard deviation through GARCH in mean models. They evidenced that the GARCH in mean model with a conditional student-t density fits the data well. They also indicate that the estimated models exhibit very weak evidence for a statistically significant relationship between a stock portfolio's return and its own volatility contrary to most asset pricing models that postulate a positive relationship between a stock portfolio's expected returns and risk.

Nelson (1991) proposes an alternative model of EGARCH to standard GARCH model to capture asymmetry and eliminate drawbacks of GARCH model and uses EGARCH model for estimating a model of the risk premium on the CRSP Value-Weighted Market Index from 1962 to 1987. He finds a negatively correlated risk premium with conditional variance. Also highly significant asymmetry coefficient of EGARCH estimates indicate that volatility tends to rise (fall) when returns surprises are negative (positive).

Blenman, Chatterjee and Ayadi (2003) investigates volatility persistence and market anomalies in daily returns of Latin American stock markets, namely, the Argentina, Brazil, Chile, Peru, Venezuela via EGARCH-M model. They find significant evidence of volatility persistence and asymmetry. Moreover, estimation results indicate the evidence in favor of leverage effect implying asymmetric volatility.

Yeh and Lee (2000) conducts a research about volatility asymmetry in the stock markets of Greater China area including Taiwan, Hong Kong, Shanghai, Shenzhen by using GARCH and GJR GARCH models. In accordance with previous researches, it is evidenced that Taiwan and Hong Kong stock markets have asymmetry behaviors implying that the impact of bad news on future volatility is greater than the impact of good news of the same magnitude. However, interestingly, the Shanghai and the Shenzhen markets exactly react opposite of those markets implying good-news-chasing behavior of the investors.

Friedmann and Sanddorf-Köhle (2002) also model the Chinese stock market returns by using GJR-GARCH and EGARCH models with generalized error distribution. They find evidence in favor of existence of stronger volatility response to bad news for the A-share indices and the Composite indices. However, they find an adverse asymmetric reaction with good news increasing the volatility more than bad news in Shenzhen B-shares as documented by Yeh and Lee (1997). Finally, they find no evidence confirming that the GJR-GARCH model is superior to the EGARCH model.

Al-Zoubi and Kh.Al-Zu'bi (2007) attempts to analyze the market efficiency, asymmetric effect and time varying risk–return relationship for daily stock returns of Amman Stock Exchange through the estimation procedure of GARCH, EGARCH, and TARCH models. Preliminary analyses of returns show that stock returns have negative skewness, excess kurtosis and deviation from normality for the Amman stock index. Moreover, they suggest that serial correlation and ARMA process lead market inefficiency due to enabling futures prices to be forecastable based on past prices. Also they evidence that The EGARCH model captures the asymmetric effect of Amman Stock Exchange.

Leeves (2007) searches the volatility characteristics of asymmetry in Indonesia Stock Exchange covering the period from 1990 through 1999 in help of three asymmetric volatility models of GJR GARCH, non linear symmetric GARCH (hereafter NGARCH), AGARCH. Estimation results suggest the time varying and asymmetric volatility in the Indonesia stock market

Henry (1998) models and analyzes the symmetric effect the daily returns of Hong Kong Exchange sampled daily from 1990 to 1995 through using GARCH, EGARCH, and and generalized quadratic GARCH (hereafter GQARCH) models. He indicates that EGARCH (1, 1) provides relatively weak estimation results due to over sensitivity to extremely large positive and negative shocks. Thus, GQARCH model outperforms all the other models in terms of fitting data and capturing the asymmetry effect.

Siourounis (2002) evaluates the performance of GARCH(1,1), Log GARCH (hereafter LGARCH) (1,1), and EGARCH-M(1,1) in terms of fitting to data on the daily return of the Athens Stock Exchange general price index sampled from 1 January 1988 to 30 October 1998. Although EGARCH model results indicate the existence of the symmetry; he finds asymmetry in a further investigation via LGARCH model in which the dummy variable of negative residual are included.

Bond (2000) runs a survey on comparing four asymmetric forms of conditional density functions of the skewed t of Hansen (1994), the non-central t of Harvey and Siddique (1999), the Gram-Charlier model of Lee and Tse (1991) and a model based on the Double Gamma density function via employing GARCH (1, 1) model on the small company returns in the UK stock market. He states that models allowing for skewness in the conditional density appear to provide a superior fit of the data than symmetric models and shows the skewed t model of Hansen is the most attractive one.

Dean and Waff (2004) conduct a study on determining whether conditional covariance decreases with good news and increases with bad news like volatility via estimating EGARCH models on both daily returns for individual stocks and weekly industry portfolios for Australian equity series covering the period from 5 January 1988 to 25 November 1999. They find strong volatility persistence and significant asymmetric volatility of market return meaning conditional market volatility increases less with positive market return shocks and expected return shocks than negative market return shocks and unexpected large shocks. Moreover, they state that market return is leptokurtic.

Alagidede and Panagiotidis (2006) analyze asymmetry and calendar anomalies in returns of Ghana Stock Exchange, which is the unique exchange being open three days in a week, covering the period 15 June 1994 to 28 April 2004. They conclude that shocks to the conditional variance will be highly persistent and stock returns have price asymmetry on Threshold GARCH (hereafter TGARCH), but not on EGARCH and calendar anomalies accommodated with running GARCH, EGARCH, and TGARCH models. Also, Frimpong and Oteng-Abayie (2006) conduct a research to model and forecast Ghana Stock exchange using the same models along with random walk (hereafter RW) model as Alagidede et al (2006) and find that the persistence in volatility is very long and explosive suggestive of an integrated process and asymmetry effect based on TGARCH, not on EGARCH, in accordance with the results of Alagidede and Panagiotidis (2006). According to the forecasting performance results, that the symmetric GARCH (1,1) model outperforms all the other models, but the EGARCH (1,1) model carries out the least in forecasting the conditional volatility of the DSI returns.

Bohl and Reitz (2006) investigated the impact of positive feedback trading in index returns of Germany's stock market segment for stocks of young, growth oriented firms, called Neuer Markt, for daily data covering from 2 January 1998 to 30 December 2002 by using the model developed by Sentana and Wadhwani (1992), and EGARCH. In addition to the proof of the presence of positive feedback traders inducing negative return autocorrelation during periods of high volatility, they evidenced the existence of leveraged effect implying that volatility of Neuer Markt is lower in the bullish periods compared to bearish periods.

Erdem, Arslan and Erdem, (2005) exert a study on examining volatility spillovers to ISE indices from inflation, interest rate, exchange rate, M1 money supply and industrial production by employing EGARCH models on monthly data from January 1991 to January 2004. They indicate direct and indirect spillovers among macroeconomic variables and stock market indices. Moreover, they provide the significant evidence of positive asymmetric effect parameter for ISE100, ISEFIN, inflation and negative for industrial production. Positive coefficient of asymmetry parameter shows that a positive shock does not have the same effect as a negative shock of the same magnitude. Mainly, a negative shock increases volatility less than a positive shock.

Issler (1999) analyzes the daily return and conditional variance Brazilian stock market indices, a spot currency-exchange rate - R$/US$ by using GARCH, EGARCH, and TGARCH with various distributions. He concludes that the return on the US$ and on the COCOA display no asymmetry, however the returns on the CBOND and TELEBRAS have clear signs of asymmetry meaning the leverage effect for the variance. Also he indicates that in terms of forecasting, the best model overall was the EGARCH (1,1) with normal distribution. Nevertheless, the Regime Switching ARCH (hereafter SWARCH) model did well, followed closely by the Student-t GARCH (1,1) in terms of goodness-of-fit statistics.

Pereira (2004) models the Portuguese Stock Market volatility series obtained from Portuguese Stock Index and a sample of fifteen stocks traded in this market representing 96% of the market index covering 1 October 1998 to the 18 May 2004 and evaluates various volatility models including GARCH (1, 1), EGARCH (1, 1), GJR-GARCH (1, 1) based on both symmetric and asymmetric error statistics. He finds no leverage effect after running EGARCH (1, 1), GJR-GARCH (1, 1), except of market index, implying the news do not display asymmetry property. Also he indicates that EGARCH (1, 1) model outperforms all others in terms of goodness-of-fit statistics. Pereira (2004) states that sum of the estimated coefficients of GARCH (1, 1) model that is close the unity could be a sign of long memory specification.

There is a vast literature evaluating forecast performance of short memory models as well as long memory models. These papers generally use forecasting accuracy criteria, such as mean error (ME), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE).

Degiannakis (2004) conducts an extensive research about modeling as well as one-step-ahead and value-at-risk forecasting of France, German and UK stock index daily returns in the period from 10 July 1987 to 30 June 2003 via GARCH, IGARCH, APARCH, and FIAPARCH models with normal and student's t distributions. Degiannakis (2004) states that the FIAPARCH (1, 1) model with student's t distribution outperforms all the other models in terms of one-day-ahead volatility forecasts. He indicates that predicting the one-step-ahead volatility is vital for measuring and managing investment risk more accurately. Consequently, portfolio managers should take into account of the ability of volatility specifications, such as the FIAPARCH (1, 1) model with student's t distribution, to forecast one-day ahead volatility more definitely.

Taylor (2004) introduces a new smooth transition exponential smoothing method and forecasts daily and weekly index returns of Amsterdam, Frankfurt, Hong Kong, London, New York, Paris, Singapore, and Tokyo stock markets from 30 December 1987 to 30 August 1995 by means of linear and nonlinear variants of GARCH model including GARCH (1, 1), IGARCH, GJR GARCH the logistic smooth transition GARCH (hereafter LSTGARCH), exponential smooth transition GARCH model (hereafter ESTGARCH) compared with it. He indicates that IGARCH and GJRGARCH models provide superior forecasts than the five GARCH models estimated using weekly returns. Based on GJR GARCH model, he finds significant evidence in favor of the leverage effect in stock returns. However, LSTGARCH and ESTGARCH model s provide weaker and upsetting estimation results in terms of evaluating forecasting performance. Interestingly, the GJRGARCH (1, 1) model estimated using daily returns provide more accurate forecasts than all five GARCH models estimated using weekly returns.

Balaban, Bayar and Waff (2006) examine the out-of-sample forecasting performance of eleven models for monthly volatility in daily returns of fifteen stock market indices (Belgium; Canada; Denmark; Finland; Germany; Hong Kong; Italy; Japan; Malaysia; Netherlands; Philippines; Singapore; Thailand; the UK; and the US) covering the period from December 1987 to December 1997 based on both symmetric (mean absolute error, root mean squared error, and mean absolute percentage error) and asymmetric error statistics. They state that while exponential smoothing model outperforms all the other models according to the symmetric error statistics, ARCH-type models exhibit best performance in case of using asymmetric error statistics

Franses and Van Dijk (1996) evaluate the forecasting performance of the GARCH model with its nonlinear versions of Engle and Ng's (1993) Quadratic GARCH (hereafter QGARCH) and GJR-GARCH on the weekly returns of Germany, the Netherlands, Spain, Italy, and Sweden stock market indices covering the period from 1986 to 1994. They conclude that QGARCH is a superior model for forecasting except that estimation sample contains utmost observations like 987 stock market crash, and recommend not using GJR-GARCH for forecasting.

Forte and Manera (2004) evaluate the forecasting performance of asymmetric GARCH models including VS-GARCH, GJR-GARCH and Q-GARCH, with the symmetric GARCH (1, 1) model as the benchmark on the three Asian as well as ten European stock market indices, namely Hong Kong, Singapore, Japan, the UK, France, Germany, Italy, Belgium, Switzerland, Greece, Portugal, Spain and Holland. They indicate that nonlinear models provide more accurate forecasts than the linear model due to the ignorance of the asymmetry of returns in the linear models.

Chen, Gerlach and So (2006) conduct a study on modeling mean and volatility asymmetry in the daily index returns of six stock markets consisting the UK, France, Germany, Italy, Canada, Australia, and Japan from 4 January 1994, to 30

September 2004 through GJR GARCH, double threshold GARCH (hereafter DTGARCH). The DTGARCH model added US market news as threshold variable called DTXGARCH. They show that volatility in six markets exhibits high persistence and long memory. They indicate the fact that all European markets investigated also shows an asymmetric mean reversion pattern in reaction to the US news and this reveals that these markets decline much faster following bad the US news. Canada stock market exhibits high persistence in volatility and small positive mean persistence and reacts asymmetrically to negative local market shock. Finally they evidenced that GJR-GARCH and DTGARCH provides weaker results than DTXGARCH.

De Santis and Imrohoroğlu (1993) analyze the dynamic manners of volatility and weekly stock returns of emerging market including Europe/Mideast economies of Greece, Jordan, Portugal, Turkey; Asia economies of India, Korea, Malaysia, Pakistan, Philippines, Taiwan/China, Thailand; and Latin America economies of Argentina, Brazil, Chile, Colombia, Mexico, Venezuela compared with the mature markets of US, Germany, Japan, and UK on the data covering the period from December 1988 to May 1994 by means of AR(1)-GARCH(1, 1) and AR(1)-GARCH(1, 1)-M model with generalized error distribution. They make some remarkable contribution to the literature. First, predictable time varying volatility is a common characteristic for almost countries. Second, in order to improve the performance of fitting to the data, a fat tailed distribution could be used. Third, investors are not rewarded for market-wide risk. Finally, they find no evidence of existence of systematic effect of liberalization on stock market volatility.

Evans and McMillan (2007) compare the forecasting ability of nine GARCH-class models and pre-GARCH models of Historical Mean, Random Walk, Moving Average, and Exponential Smoothing on the daily stock market returns of 33 economies from 1 January 1994 to 22 April 2005 including Turkey. According to the results, GARCH-class models provide superior forecasting results in 23 economies while the moving average model gets better forecasting results in 9 countries including Turkey. Philippines stock market returns are forecasted better via exponential smoothing.

Suleyman (2000) makes a comparison between linear GARCH (1, 1) and non-linear EGARCH(1, 1) models due to proven fact that non linear models are superior for both modeling and forecasting than linear models when the variable has skewed distribution. He uses the monthly stock market returns of seven emerging countries of Argentina, Brazil, Colombia, Malaysia, Mexico, the Philippines, Taiwan from February 1988 to December 1996, and surprisingly finds that linear GARCH (1, 1) model outperforms EGARCH (1, 1) albeit return series has skewed distribution.

Ogum, Beer and Nouyrigat (2005) analyze Johannesburg Stock Exchange, Nairobi Stock Exchange, and Lagos Stock Exchange in terms of efficiency, asymmetry, and auto regressive behavior by means of EGARCH model in a similar methodology of Chortareas et al (2000). Results show that volatility in investigated stock markets are persistent leading these markets to be inefficient. In terms of asymmetry, Kenya has a positive asymmetry character implying that positive shocks increases volatility more than negative shocks of an equal magnitude while South Africa and Nigeria have negative asymmetry property, called the leverage effect.

Hansen, Lunde and Nason (2003) propose the model set confidence procedure (hereafter MCS) to choose best volatility models. MCS is a method resembling to the confidence interval approach in that the MCS method chooses the best volatility model with a certain probability specified by the user. The main property of the MCS is acknowledging the limitations of the information in the data. They estimate and forecast on the daily returns on the Standard & Poor's Depository Receipts (hereafter SPYDER) from 3 January 1995 to 28 February 2002 via fifty-five volatility models, then evaluate these models in terms of MCS method. Based on MCS method with the mean absolute deviation loss function, only VGARCH model is selected over the other volatility models. They indicate that MCS method could be used for detecting superior volatility models. Additionally, they conduct a simulation study resulting that the MCS yields a set of models that contains all, or almost all, truly superior models, however, rarely, exactly, captures the true set of superior models, if the difference in expected performance of superior and inferior models is small. Thus, they state that the MCS represents a strong method to select the best set of forecasting models.

Pagan and Schwert (1990) focus on comparing different volatility models of GARCH (1, 2), EGARCH (1, 2), and regime switching GARCH (hereafter RS-GARCH) with US stock return data from 1834 to 1925. Based on estimation results, GARCH and RS-GARCH have weak explanatory power on the data; however, EGARCH model is the best model for forecasting.

Lanne and Saikkonen (2004) exert an effort to model US stock returns and investigate the relationship between risk and return in monthly postwar U.S. stock market data from January 1946 to December 2002 through GARCH based models with various distributions. They propose the GJR GARCH model with z distribution capturing skewness of data and find a significant and positive relationship, contrary to previous researches, while the standard GARCH-M with t distribution model and its asymmetric counterpart of GJR-GARCH with t distribution model could not capture skewness and find the relationship.

Berchtold (2005) offers to substitute the daily pseudo realized volatility (hereafter PRV) for the daily close-to-close realized volatility (hereafter CCRV) and forecasts daily US stock index returns starting at 1 January 1998 and ending at 31 March 2005 with the help of GARCH(1,1), GJR-GARCH(1,1) and E-GARCH(1,1) models. He states that models with realized volatility provide surprisingly accurate one – step - ahead forecasts, however, volatility forecasts with PRV are found to be more accurate than those of with CCRV. Consequently, he suggest, in practical situations, to use PRV in case of unavailability of intraday data set. Finally he indicates that researchers, regulators, risk managers and investors should rise to notice the pseudo realized volatility measure.

Akgiray (1989) applies volatility forecasting models of GARCH (1,1), ARCH (2), EWMA and Historical Volatility (hereafter HIS) on daily returns of the CRSP value-weighted and equal-weighted indices covering the period from January 1963 to December 1986. He declares that time series of daily stock returns displays significant levels of dependence. Moreover, he finds that GARCH (1,1) model surpasses the others in terms of fitting to data and out-of-sample forecasting evaluated via ME, RMSE, MAE, MAPE.

McMillan, Speight and Apgwilym (2000) compare the forecasting performance of several volatility models including the historical mean, moving average, random walk, exponential smoothing, exponentially weighted moving average, simple regression, GARCH, TGARCH, EGARCH, and CGARCH models, and, additionally, recursive variants of these models where appropriate on the various frequencies of UK stock market indices from 2 January 1984 to 31 July 1996 under both symmetric and asymmetric loss functions. They provide a significant evidence that random walk model outperforms the others in monthly volatility forecasts under the symmetric loss function. Moreover, weekly volatility forecasts based on random walk, moving average, and recursive smoothing are averagely better, while daily volatility forecasts resulted from GARCH, moving average and exponential smoothing models are slightly better. Finally, they state that the moving average and GARCH models maintain the most coherent forecasting performance when attention is restricted to one forecasting method for all frequencies. Generally, they indicate that forecasting performance of GARCH models are weak consistent with other researches.

Bluhm and Jun (2001) conduct the research to forecast the volatility of the daily German stock exchange returns from 1 January 1988 to 30 June 1999 via EWMA, GARCH, GJR-GRACH, EGARCH, GARCH-M model, and Taylor's (1986) stochastic volatility (hereafter SV) models. They conclude the fact that EGARCH model that is the best in terms of fitting the data. Moreover, they indicate that there is no single method is clearly superior in terms of out-of-sample forecasting. Also, implied volatility could be used for forecasting in terms of the forecasting performance. They rule that the longer the forecast horizon becomes, the worse GARCH based models with less persistence are. They emphasize that performance of the models is dependent on the error measurements as well as the forecast horizons. Moreover, the SV and implied volatility are superior in case of option pricing although ARCH type models are the best for calculating value-at-risk.

Scheicher (1999) employs the heteroscedastic models of GARCH (1, 1), EGARCH, and RS-GARCH to model the main stock index of the Vienna Stock Exchange with daily data from 1986 to 1992. His first empirical finding is the autocorrelation in returns which could be due to strong nonsyncronous trading can be interpreted as a rejection of the Efficient Markets Hypothesis. Second, a parsimonious model from the GARCH type models can capture the statistical properties of daily returns. Third, no leverage effect and no chaotic structures are found in Vienna Stock Exchange. Fourth, GARCH works best with daily data and also a weakening of volatility clustering at lower frequencies.

Geyer (1994) attempts to model daily Vienna stock market index over the period January 1986 to August 1992 with using traditional models of ARFIMA and integrated moving average model (IMA) along with GARCH models. Geyer (1994) states GARCH and IMA models point out the persistent volatility, and also Geyer (1994) provides evidence in favor of the fact that highly persistent volatility may be due to neglected structural changes. Also it is evident that Both IMA and GARCH models yield similar out-of-sample forecasts.

Chortareas, McDermott and Ritsatos (2000) conduct a detailed research about time series properties such as asymmetry, conditional variance risk premium, and autoregressive process of daily returns of the Athens Stock Exchange composite index covering the period from January 1, 1987 through June 30, 1997 based on the EGARCH model. They provide significant evidence of time dependence implying return predictability, asymmetry, and significant risk premium for conditional variance.

Also Apergis and Eleptheriou (2001) attempt to model the Athens Stock excess daily stock returns over the period from January 1990 to July 1999 via evaluating GARCH-typed models of GARCH-M, EGARCH, GJR, GQARCH models in terms of fitting to data. The asymmetric GQARCH (1, 2) model outperforms all the other models. Moreover, volatility clustering and leverage effect are proved to be significant implying higher volatility during market booms than market declines.

Leon and Mora (1999) model the daily Spanish stock exchange returns starting January 1987 ending June 1995 via estimating variants of the GARCH models. They find that the models capturing the asymmetry effect, especially AGARCH and TGARCH, produce superior results. Interestingly, both stochastic volatility and Poisson Jump Diffusion models provide less accurate estimations than asymmetric GARCH based models. Finally, they evidenced that contrary to the other studies, models with t distribution could not outperform those of with normal distributions.

Kasch-Haroutounian and Price (2001) make an attempt at modeling volatility of the four emerging markets of Central Europe including the Czech Republic, Hungary, Poland and Slovakia via GARCH(1, 1), EGARCH(1, 1), GJR-GARCH, Engle and Bollerslev' s (1986) NGARCH(1, 1), AGARCH(1,1) by Engle (1990), the NAGARCH, and the VGARCH models. Based on VGARCH, long memory property is found to be significant for the Czech Republic, Slovakia, and Poland. Strong GARCH effects are observed in all series examined. They also state that the leverage effect is captured for Hungary and the Czech Republic. Moreover, they find significant conditional correlations between two pairs of countries: Hungary and Poland, and Hungary and the Czech Republic through multivariate GARCH models.

Michelfelder and Pandya (2005) evaluate the predictability of volatility of seven developing markets for six countries (India, Hong Kong, South Korea, Malaysia, Singapore, and Taiwan) compared with developed markets of the US and Japan via employing EGARCH with skewed generalized error distribution model on daily stock index returns from 2 July 1997 to 2 October 2001. They indicate that emerging markets do not follow a random walk implying the fact that these markets are predictable and thus these markets are not efficient while developed markets follow a random walk. In accordance with previous researches, they find that volatility of the other emerging exchanges is comparatively higher than the volatility of the Japan and U.S. stock exchanges. None of the markets except for the India has a significant risk premium. Finally, they conclude that shocks occurring in the US are transferred into the rest of the world based on the result of the volatility modeling process and shock transfer transmission mechanisms.

Shamiri and Hassan (2005) model and forecast the two Asian stock market indices, Malaysia and Singapore, starting on 2 January 1991 and ending on 31 December 2004 through GARCH, EGARCH and GJR-GARCH with distributions of Gaussian normal, Student-t, and Generalized Error Distribution. They conclude that asymmetric EGARCH and GJR-GARCH models, especially with student-t distributions are considered, are superior to symmetric GARCH model. Additionally, it is provided that AR (1) - GJR GARCH model and AR (1) EGARCH models provide more accurate results for the Malaysian stock market and the Singaporean stock market, respectively. They find that both of the market volatilities are highly persistent implying the existence of volatility and have the leverage effect. It is evidenced that student-t distribution is the best in terms of fitting-to-data and capturing the properties of the returns.

Kuen and Hoong (1992) model the variance of Singapore Stock Exchange indices covering the period from 19 March 1975 to 25 October 1988 by employing EWMA and GARCH models and evaluate these models in terms of out-of-sample forecasting. They evidenced the superiority of EWMA model. Additionally, they indicate that poorest performance of GARCH model could take root from the strict data and model convergence requirements.

Xu (1999) efforts to model the volatility of daily Shanghai Stock Market returns covering the period from 21 May 1992 to 14 July 1995 through GARCH, EGARCH, and GJR-GARCH models. Based on preliminary analysis of data, he provides the evidence of dependence, non-normality, thick tails and volatility clustering leading him to use conditional heteroscedastic models. There is no asymmetry effect found through EGARCH and GJR- GARCH. He indicates that governmental policy on stock markets could be the fundamental reason of volatility in Shanghai's stock market.

Chen (2003) employs GARCH, GJR – GARCH, and EGARCH models with in mean specification under the various distribution assumptions of normal, standardized logistic, student-t, and generalized error distributions to model the daily returns of the Taiwan Stock Exchange weighted index starting 1 January 1992 ending 31 December 2001. It is found that the model producing most accurate results is EGARCH in mean with generalized error distribution in terms of capturing the dynamic behavior consisting serial correlation, volatility clustering, asymmetric volatility, and ARCH-in-mean and a symmetric and leptokurtic innovation distribution in the Taiwan stock index. Although GARCH with normal distribution and RiskMetrics do not considerably maintain inferior results for predicting the whole return distribution, EGARCH in mean with generalized error distribution model predicts the fat tailed distribution in the stock market returns. This indicating the fact that risk managers and investors computing the VaR and other risk management applications about the Taiwan stock index returns should use EGARCH in mean with generalized error distribution model to get more accurate results.

Fabozzi, Tunaru and Wu (2004) exerts effort to model daily Chinese equity data traded in Shenzhen and Shanghai markets sampling from 1 November 1992 to 1 November 2001 with help of GARCH (1, 1), GARCH-M (1, 1), and threshold GARCH models. They exemplify the fact that while TGARCH (1, 1) model fits the data on the Shanghai exchange well, GARCH (1, 1) model fits to the daily data on the Shenzhen exchange. Thus they indicate that these two models capturing the dynamics of the volatility can be used for risk management purposes. Additionally, they evidenced that the rates of change for the two market variances are different based on forecast results.

Rousan and Al-Khouri (2005) exert a study on designing a volatility model for daily return of Amman Stock Exchange Composite Index from 1 January 1992 through 31 December 2004. Preliminary analysis' results of non normality, serial correlation channel them to use conditional heteroscedastic models. Thus, applying symmetric models of ARCH and GARCH along with asymmetric GJR-GARCH and EGARCH, they have significant evidence that Amman stock market has no asymmetry but it is very persistent leading the market inefficiency. Moreover they state that GJR-GARCH model outperforms all the other models in terms of capturing return characteristics.

Hassan, Al-Sultan and Al-Saleem (2003) model Kuwait Stock Exchange and examine stock market efficiency through GARCH and EGARCH models on the daily data from 1995 to 2000. They find that Kuwait Stock Exchange is inefficient and has an asymmetric property.

Pandey (2003) attempts to model and forecast high frequency data of Mumbai stock exchange. He employs the volatility models of GARCH (1, 1) and EGARCH (1, 1) with traditional and extreme-value estimators over different time periods and compares them with realized volatility constructed by using high frequency data. He indicates that the index has the properties of persistence and is mean – reverting. Also he concludes extreme-value estimators are more efficient estimators of realized volatility although conditional volatility models provide less biased estimates. In terms of volatility forecasting performance, extreme value estimators outperform the conditional volatility models.

Karmakar (2007) exerts a research about analyzing heteroscedatic characteristics of the Indian Stock Market returns covering the period from 2 July 1990 to 31 December 2004 through using various GARCH models. Karmakar (2007) indicates that GARCH (1, 1) is outperformed by GARCH (2, 1) model providing the significant evidence of time varying volatility displaying clustering, high persistence and predictability. Also Karmakar (2007) finds asymmetric volatility via EGARCH (1, 1) model fitted the data well. Finally, EGARCH (2, 1) model outperforms all the other models and provides negative, but insignificant, trade-off between risk and return.

Hansen and Lunde (2005) evaluate 330 ARCH-type models in terms of out-of-sample forecasting performance on DM/$ exchange rate and IBM stock return from January 2, 1990 through May 28, 1999. They provide significant evidence that GARCH (1, 1) outperforms in case of using DM/$ exchange rate, nevertheless GARCH (1, 1) gets weaker results than other models on using stock returns. They indicate that APARCH (2,2) model of Ding et al. (1993) provide best overall performance. Finally, they state that a well performing model should take into account the leverage effect of the returns due to their superior performance of them.

Selecting the different distribution model affects the fitting-to-data and out-of-sample forecasting performance. Verhoeven and McAleer (2004) examines the effect of various distributions on GARCH models in terms of eliminating drawbacks of capturing the effects of extreme observations, outliers and skewness in returns. They provide significant evidence that GARCH models estimated with asymmetric leptokurtic distributions outperform their counterparts estimated under normality in terms of (i) detecting skewness and leptokurtosis; (ii) the maximized log-likelihood values; and (iii) isolating the ARCH and GARCH parameter estimates from the adverse effects of outliers. They finally indicate that the flexible asymmetric Student’s t-distribution is the best model for detecting the non-normal aspects of the data.

Chuang, Lu and Lee (2007) evaluate the volatility performance of GARCH model with the various distributions of exponential generalized beta type two, mixture of three normals, mixture of two normals, logistic, exponential power, mixed diffusion jump, normal, skewed generalized t, scaled student's t, SU-normal, and two-piece mixture of normals with a benchmark of RiskMetrics model. According to the estimation results on different daily returns of stock markets including Australia, Canada, China, Japan, Swiss, UK, US, and exchange rates data from 2 January 1996 to 23 October 2003, they indicate that the GARCH model with the logistic distribution and the scaled student-t distribution and the RiskMetrics provide better forecasting performance, nevertheless GARCH models with the exponential power and the mixture of two normal distributions get weaker results.

Li (2007) models the weekly returns of 30 Dow-Jones industrial stocks from 1986 to 2005 via GARCH (1, 1) model with different distributions of normal, student's t, and exponential generalized beta distribution of the second kind (or, EGB2) to account for stock return characteristics, including fat tails, peakedness (leptokurtosis), skewness, clustered conditional variance, and leverage effect. First, he evidences that all returns investigated are leptokurtic indicating that the returns are normally distributed is invalid. He finds a significant evidence of superior forecast in favor of EGB2 over the other distributions. After applying models with EGB2, he indicates that EGB2 has been decreased; this implies that the so-called leverage effect is, at least, partially a result of the model's misspecification because of the imposition of a normal distribution of return series.

CHAPTER III

DATA AND EMPIRICAL FINDINGS

The aim of this chapter is to examine the property of dual long memory in returns and volatility. The existence of long memory in returns indicates the predictability of future prices through past prices. Also long memory in returns putrefies weak form efficient market hypothesis. Long memory in volatility indicates that shock occurring in price changes remains at long lags, which damages price mechanism. Moreover occurrence of long memory suggest the use of long memory volatility models rather than short memory volatility models to model the stock market volatility. Also the impact of sudden volatility breaks on the persistence of the volatility is investigated. In this chapter, the characteristics of the data are presented, and then empirical findings are discussed.

3.1. Data

The data employed in this study are continuously compounded daily returns of the indices consisting ISE National – 100, and the sectoral indices of ISE National – Services, ISE National – Financial, ISE National – Industrials, ISE National – technology (hereafter, ISE100, ISESRV, ISEFIN, ISEIND, ISETECH, respectively) traded in Istanbul Stock Exchange. The continuously compounded daily returns are calculated by taking a logarithmic difference of indices, which is $R_{i,t} = \log(p_{i,t} / p_{i,t-1})$ where $p_{i,t}$ denotes the value of index *I* at time *t*. Although ISE100 index starts on 1st January 1986, the period between 4 January 1988 and 14 November 2007 is analyzed since the data before 4 January 1988 is inappropriate to investigate in terms of orderliness of the data. ISEFIN and ISEIND indices span from 3 January 1991 to 14 November 2007. ISESRV index covers the period from 3 January 1997 to 14 November 2007. Finally, ISETECH index is analyzed for the period 4 July 2000 to 14 November 2007. The data is obtained from the electronic data delivery system of the Central Bank. The main purpose of analyzing sectoral indices is characterizing the memory patterns of ISE deeply, thus providing more general interpretations (Blasco et al, 1996).

Figure 1 shows the ISE100 price and returns graphs. Relatively high volatility is observed during the period between the 1996 and early 2004, when some international financial crisis such as 1994-1995 Latin American, 1997 South-East Asian and Russian, 1999 Brazilian, as well as local crisis of November 2000 and 21 February 2001 occurred. ISEIND prices and returns, illustrated in Figure 2, seem to be influenced by the local and global crisis, such as emerging market crisis in terms of high volatility until the middle of 2004. Figure 3 exhibits observed ISEFIN index returns and prices. Financial index, similar to ISE100 index, is highly volatile between 1996 and 2004, corresponding to the period of financial crisis. Also, international and local crisis occurred during the period between 1997 and 2003 lead ISESRV index to be more volatile as seen in Figure 4. Finally, Figure 5 illustrates the ISETECH prices and returns. Local crisis of November 2000 and 21 February 2001 are likely to be the reason of high volatility of ISETECH occurred between 2000 and 2003.

Figure 1. graphics of daily ISE100 index prices and returns

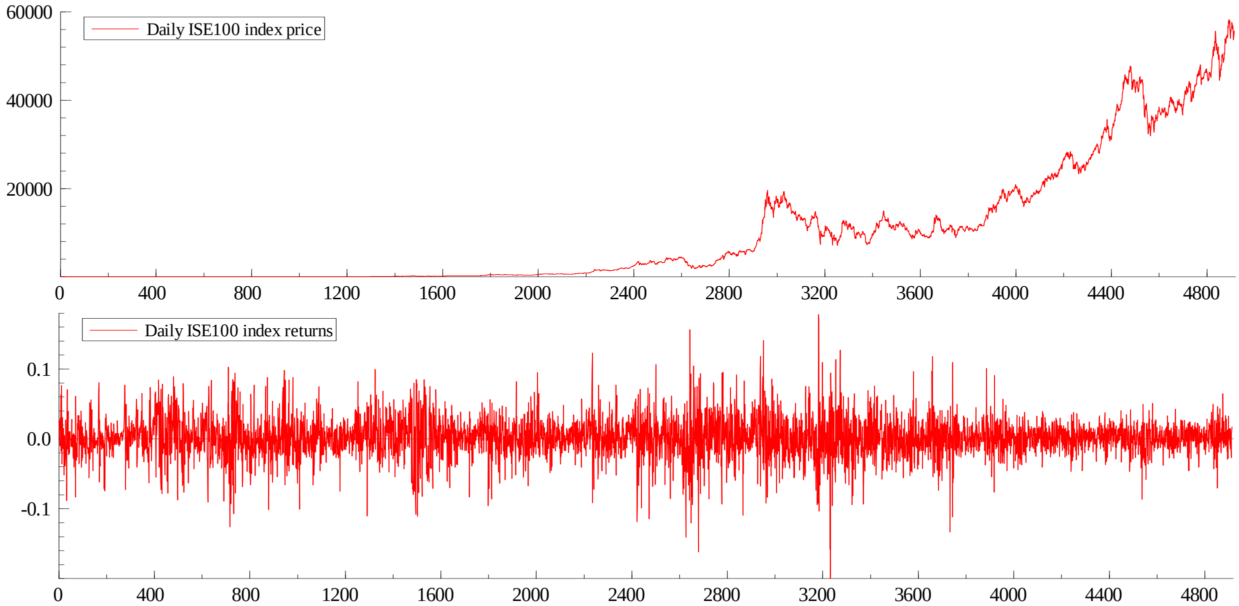


Figure 1. Graphs of daily ISE100 index prices and returns

Figure 2 graphics of daily ISEIND index prices and returns

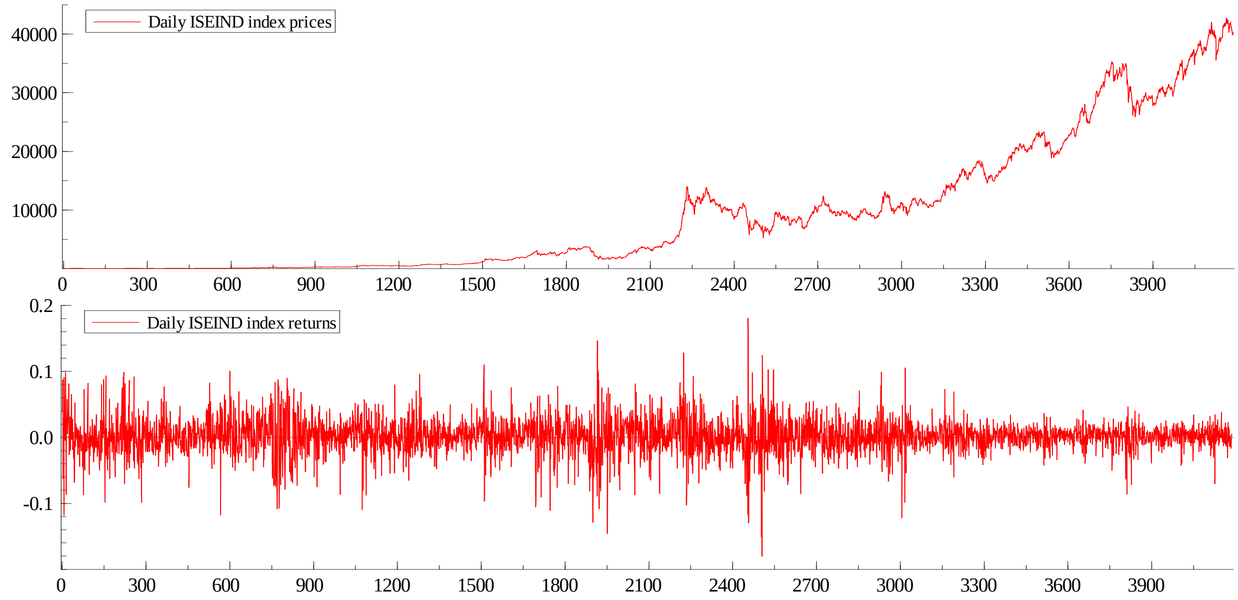


Figure 2. graphs of daily ISEIND index prices and returns

Figure 3 graphs of daily ISEFIN index prices and returns

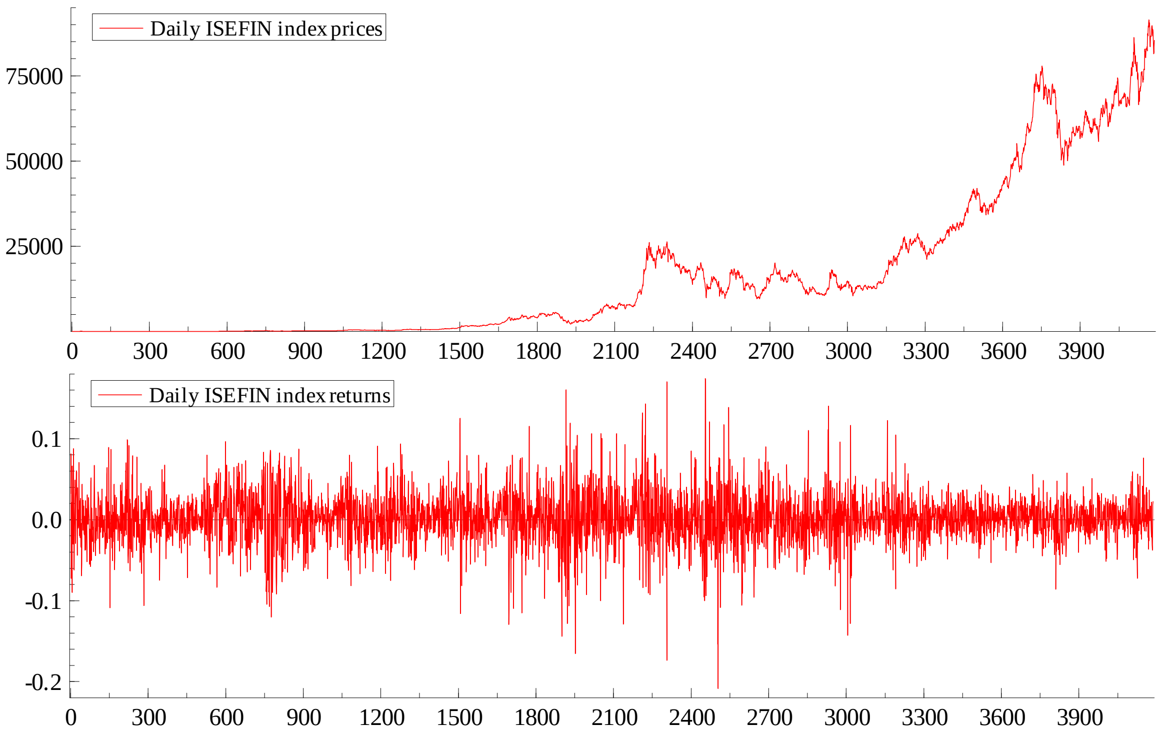


Figure 3. Graphs of daily ISEFIN index prices and returns

Figure 4 graphs of daily ISESRV index prices and returns

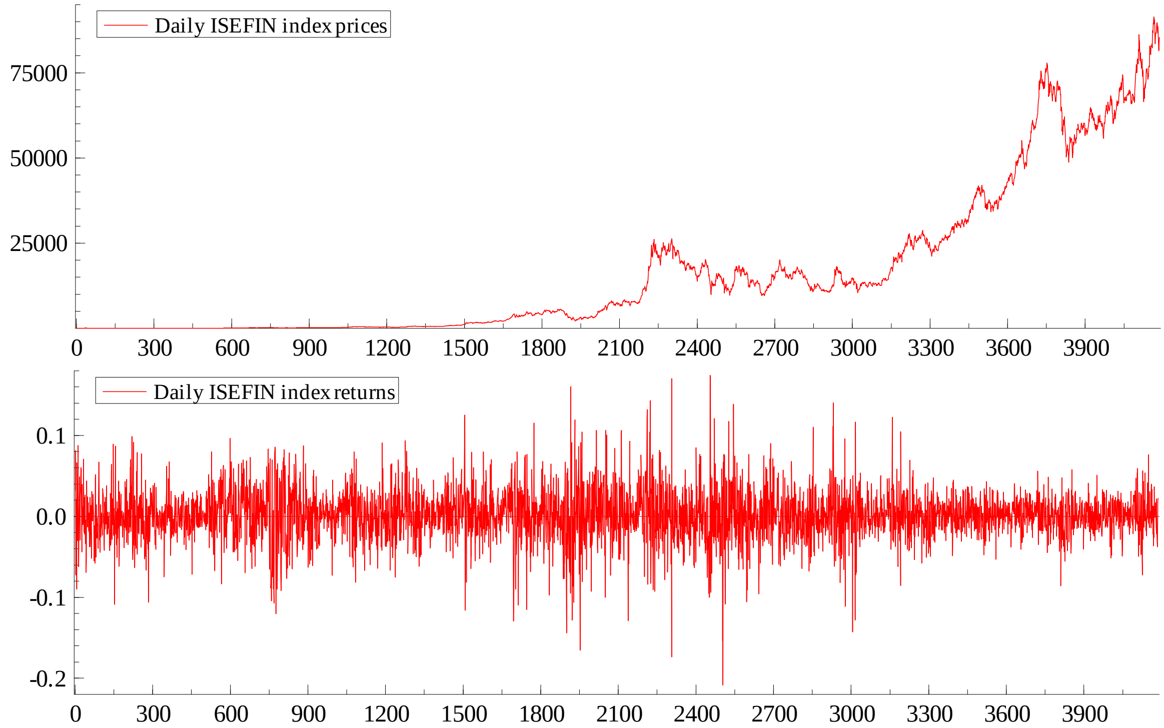


Figure 3. Graphs of daily ISEFIN index prices and returns

Figure 5 graphs of daily ISETECH index prices and returns

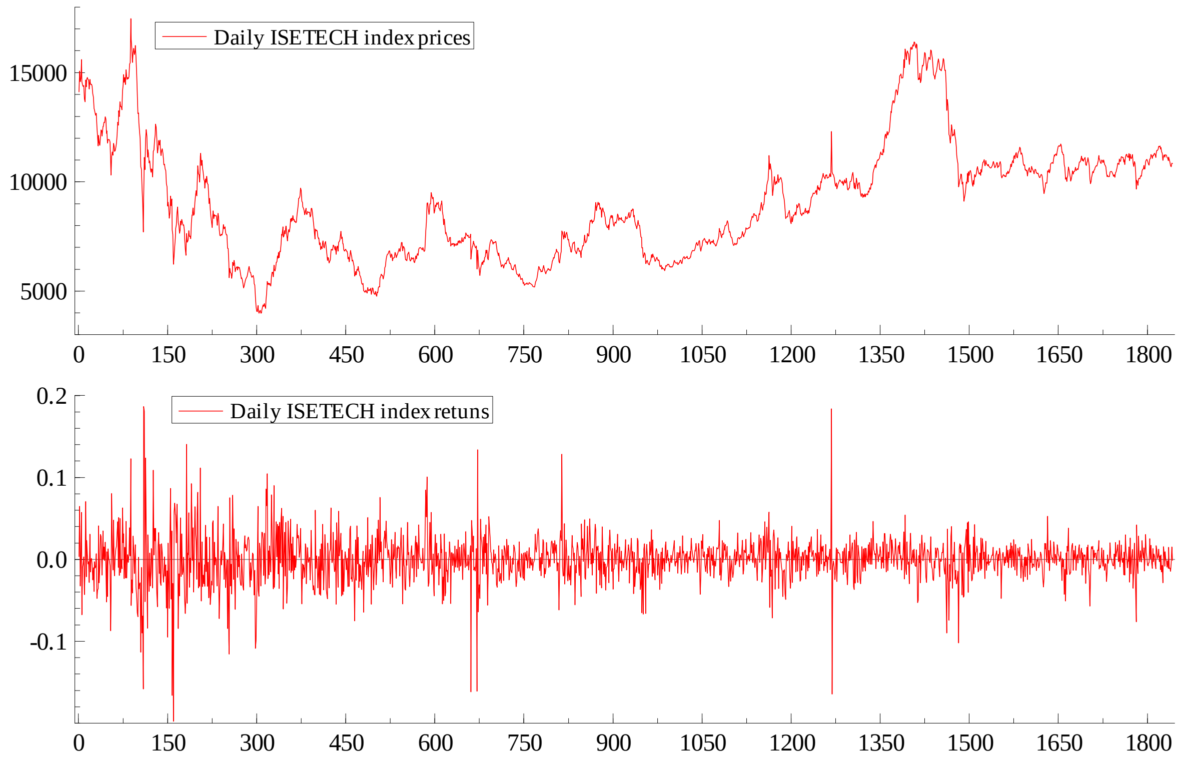


Figure 5. Graphs of daily ISETECH index prices and returns

The descriptive statistics are shown in table 1. The null hypothesis of normal distribution is rejected for all the indices based on the Jarque – Bera test. The Ljung – Box statistics in levels of the returns indicate the existence of serial correlation. Moreover, heteroscedasticity, thus the symptom of ARCH effect indicating time varying conditional distribution, is detected via the Ljung – Box statistics in squares of the returns. Though reported here, the Ljung – Box statistics in both levels and squares significant up to 200th order and small reveals the weak short memory pattern of the data indicating the dependence among distance observations. Additionally, significant the Ljung – Box statistics in returns at high lags imply the volatility clustering. Consequently, linear and nonlinear dependencies are one of the main properties of the indices returns.

Table 1. Descriptive statistics of sample return series

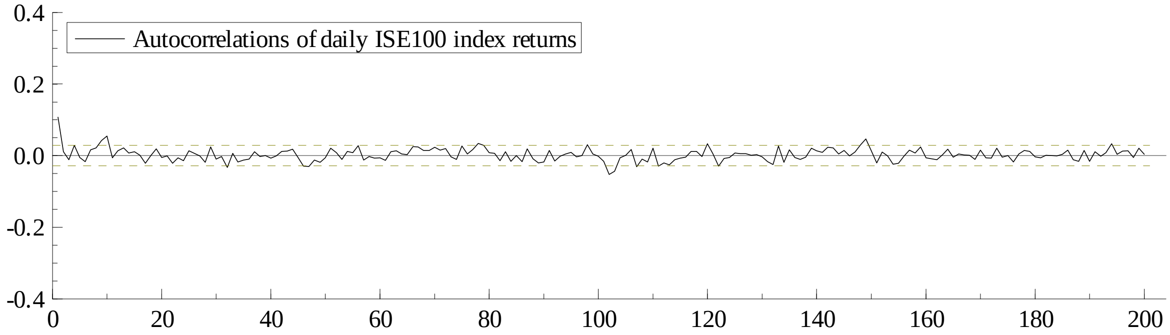
	ISE100	ISEIND	ISEFIN	ISESRV	ISETEC
No. of observation	4914	4187	4187	2697	1842
Mean	0.0018	0.0017	0.0019	0.0013	-0.0001
Standard deviation	0.0292	0.0270	0.0319	0.0286	0.0286
Skewness	-0.0607	-0.1209	-0.0236	-0.0057	-0.0841
Kurtosis	6.1757	7.0540	6.1171	8.5621	11.1477
Minimum	-0.1998	-0.1801	-0.2084	-0.1926	-0.1975
Maximum	0.1777	0.1804	0.1746	0.1733	0.1864
J-B	2067.946*	2877.434*	1695.450	3476.574*	5097.253*
$Q(10)$	91.779*	54.930*	43.196*	21.035*	30.516*
$Q(20)$	100.12*	65.162*	61.276*	36.031*	43.628*
$Q(40)$	119.49*	84.775*	87.153*	64.819*	70.045*
$Q_S(10)$	1273.2*	1440.6*	895.66*	692.02*	534.52*
$Q_S(20)$	1662.6*	1783.4*	1183.5*	812.53*	585.58*
$Q_S(40)$	2091.7*	2156.6*	1515.9*	957.45*	688.16*

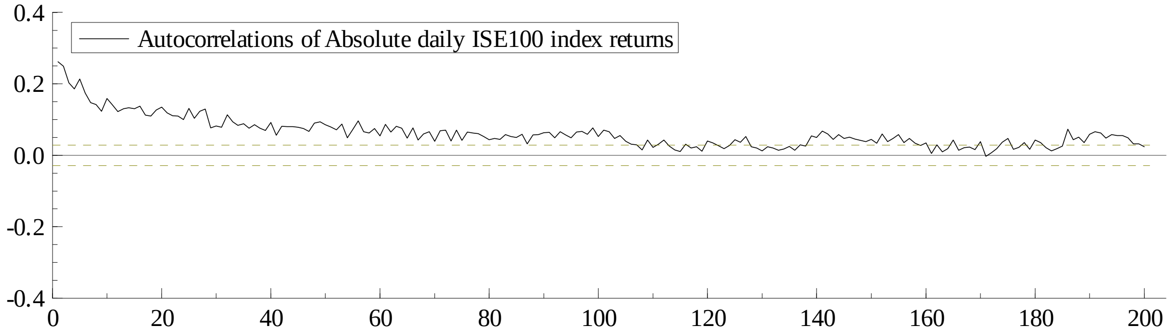
Notes: J-B denotes Jarque-Bera (1980) normality test statistic. * denotes significance at 1% level. $Q(.)$ and $Q_s(.)$ are the Ljung-Box statistic for returns and squared returns up to 10, 20, and 40 lags, respectively

Skewness measuring the symmetry of the distribution is marginally negative, indicating that distribution of the indices is skewed to the left bearably. Negative returns appearing after the crisis in Turkey could lead to negative skewness. Kurtosis is used for evaluating the peakness and fatness of the tail. Consistent with the Panas's (2001) study, the distribution of the indices is leptokurtic meaning the positive excess kurtosis. Leptokurtic distribution for ISE indices confirm the research results of Pagan (1996) revealing the existence of the positive excess kurtosis in most of the financial assets. Non normal distribution and volatility clustering imply the necessity of modeling volatility along with returns for all indices (Kang and Yoon; 2006). Ljung- Box statistics results indicating the nonlinear structure in returns suggests the hypothesis that deterministic process, such as long memory, or nonlinear stochastic process, such as chaos produce the returns (Panas; 2001).

Graphical analysis of autocorrelation functions are widely used as a preliminary test for detecting long memory. Figure 6 to figure 10 gives the graphics of autocorrelations for daily, absolute daily and squared daily returns of indices. Non synchronous trading is possibly the reason of sharply diminishing autocorrelation function of daily returns. However, autocorrelation functions of absolute daily and squared daily returns of indices remain significant during the high lags. These patterns in absolute and squared return give a hint of volatility persistence in return series. Moreover, highly autocorrelated squared returns suggests the long memory specifications (Kang and Yoon;2006).

Figure 6. Correlograms for the daily, absolute, and squared ISE100 indices returns





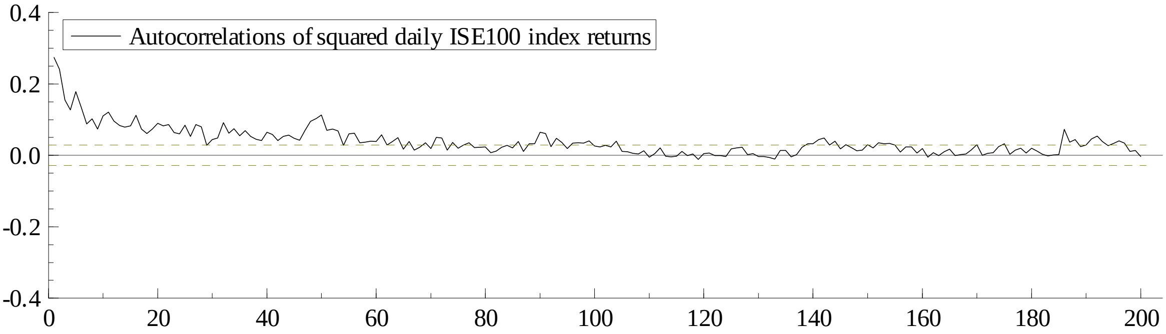


Figure 7 Correlograms for the daily, absolute, and squared ISEIND indices returns

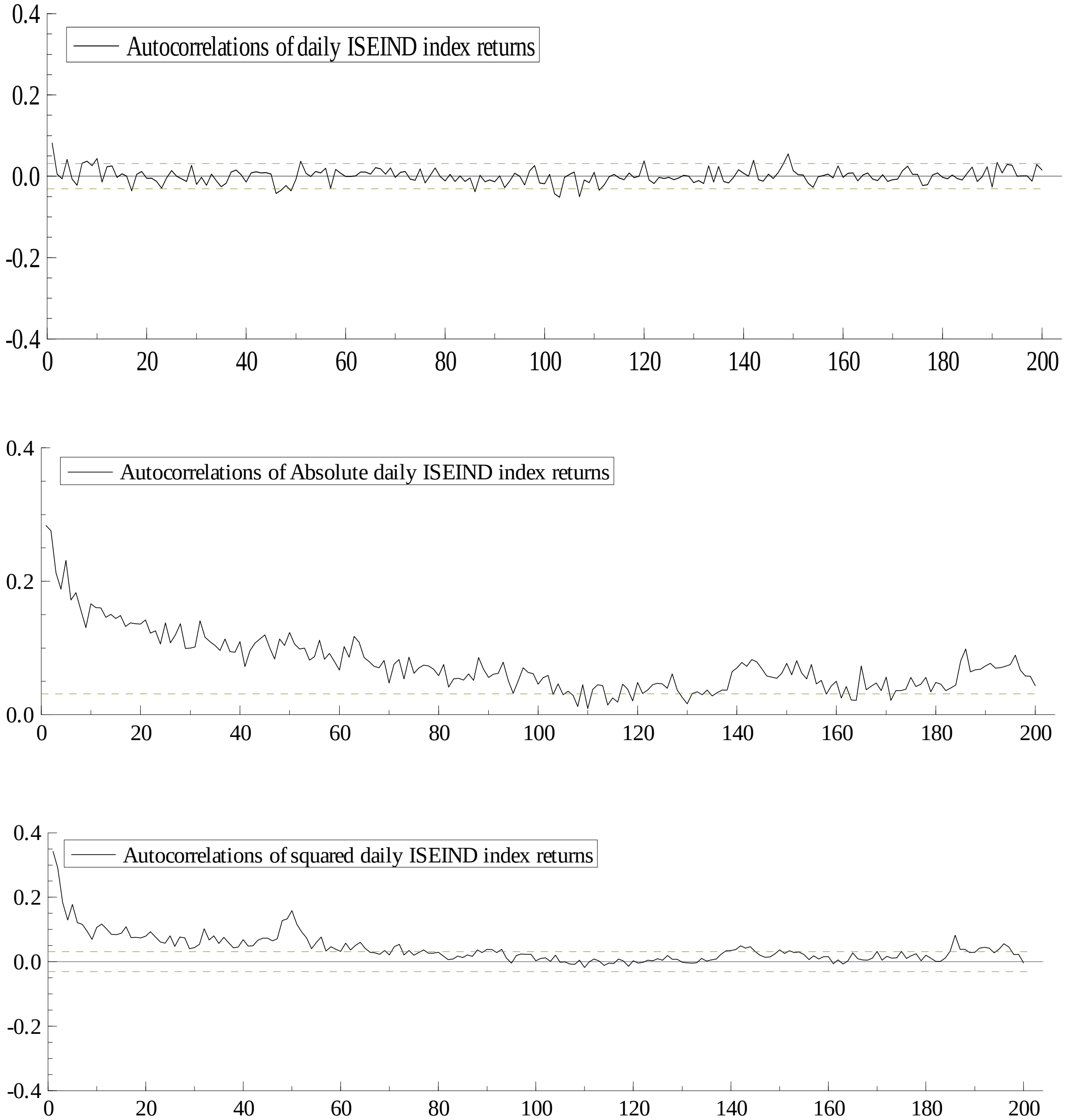
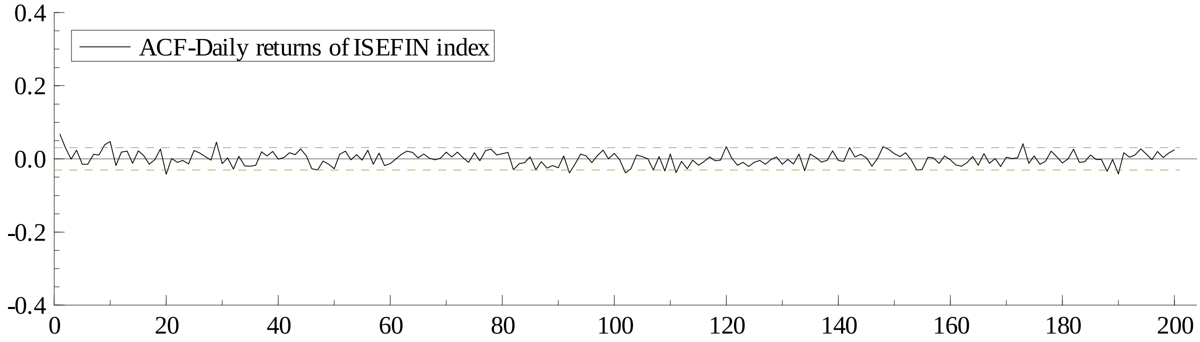
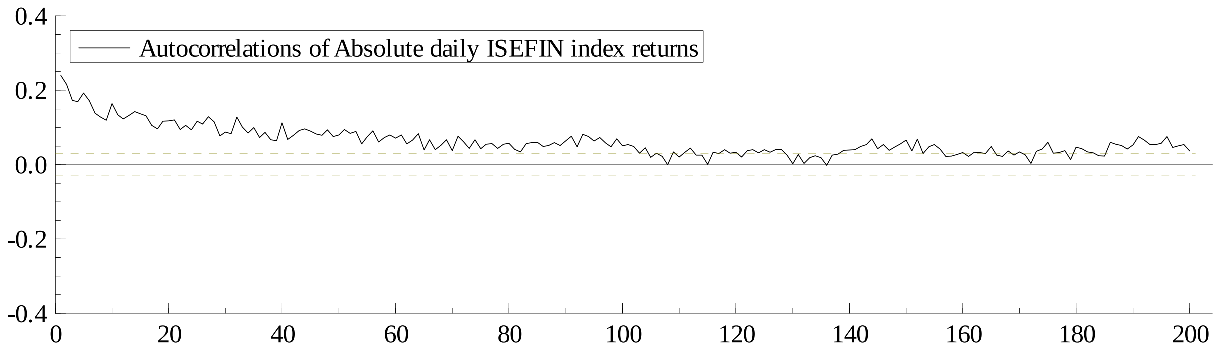


Figure 8 Correlograms for the daily, absolute, and squared ISEFIN indices returns





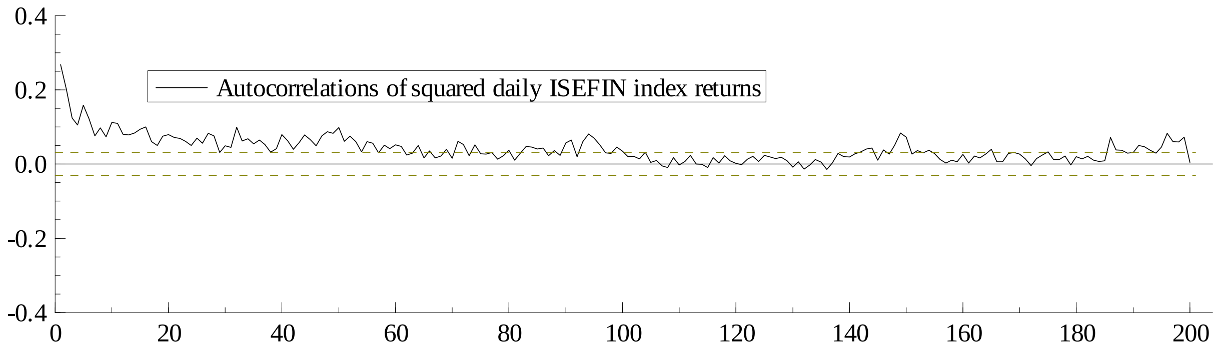
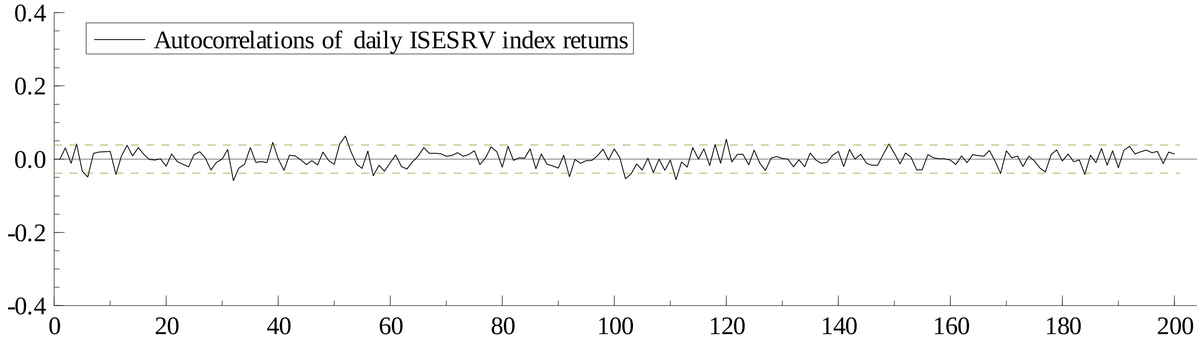
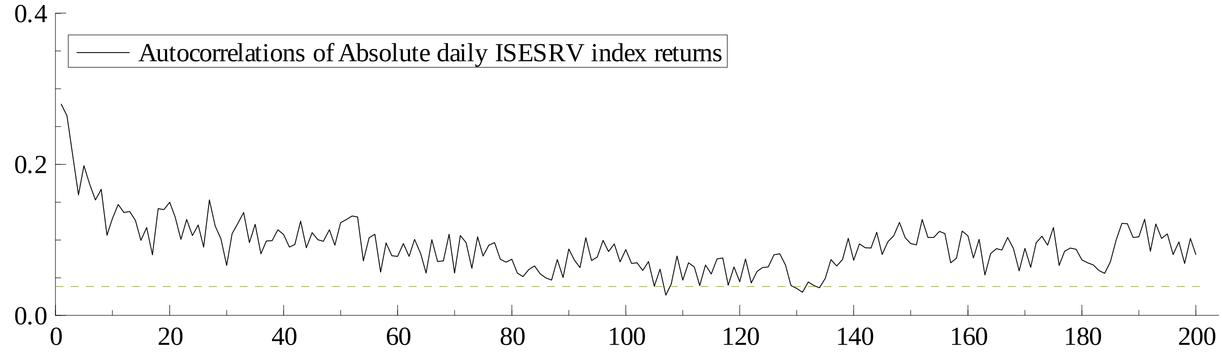


Figure 9 Correlograms for the daily, absolute, and squared ISESRV indices returns





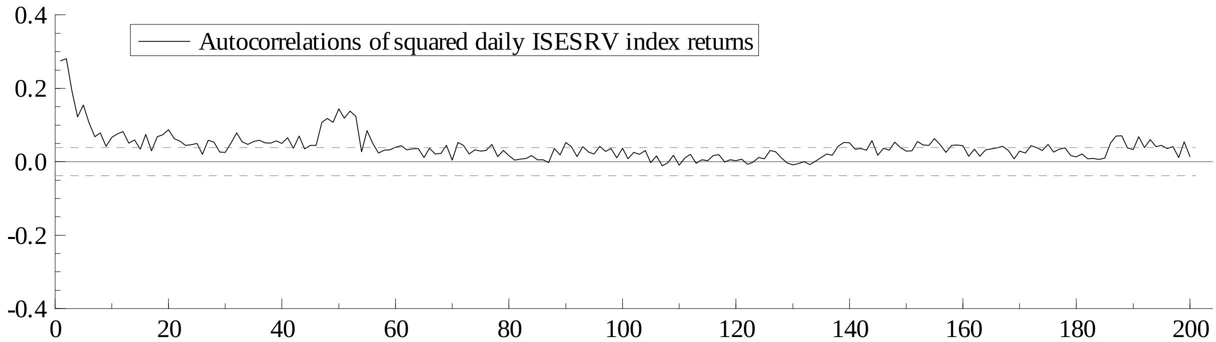
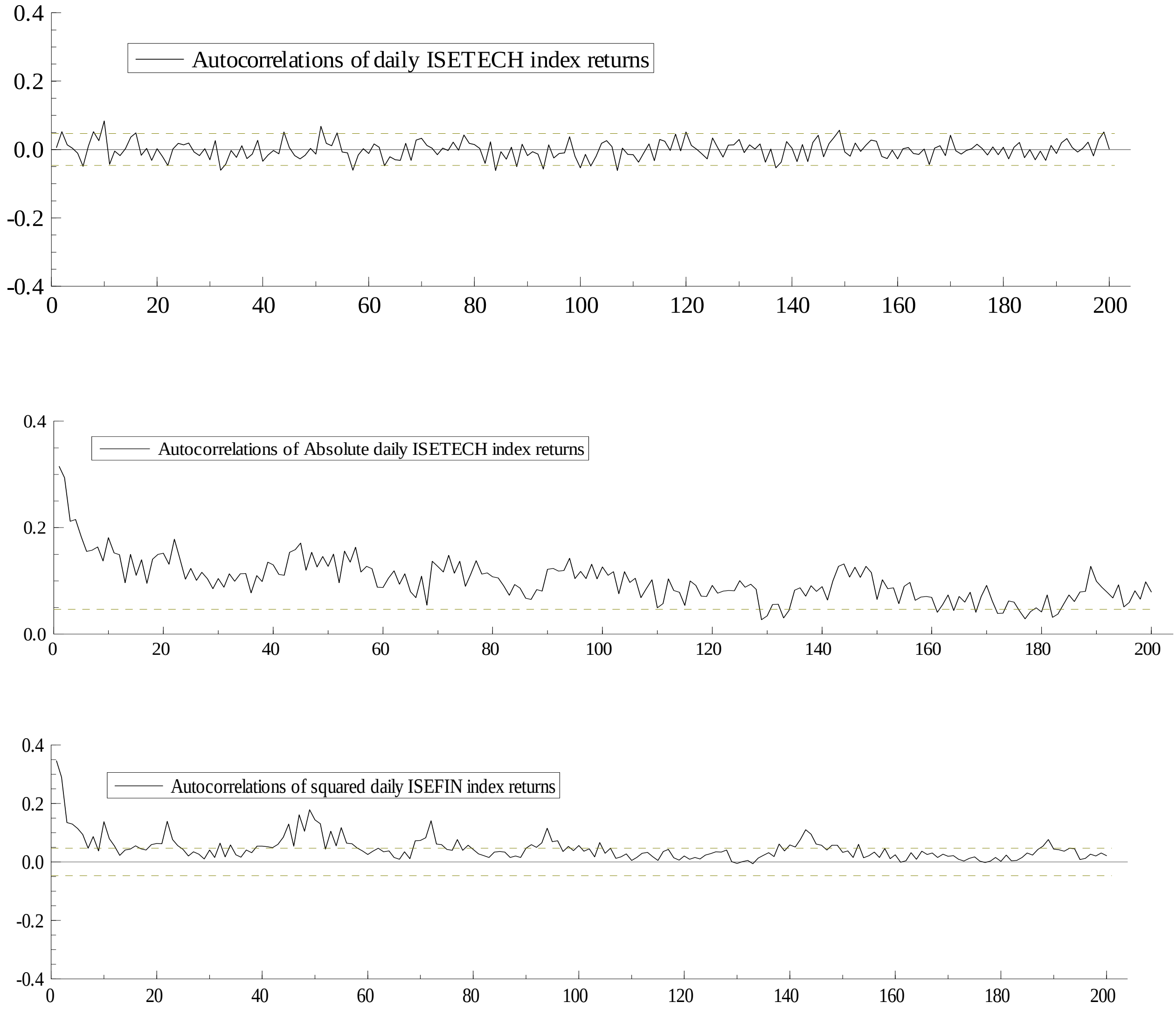


Figure 10 Correlograms for the daily, absolute, and squared ISETECH indices returns



Unit root tests are employed before detailed memory analysis. Long memory in the returns is evidenced by the existence of the unit root in a data set suggesting market inefficiency. Additionally, Stationarity warrants invariant statistical properties, thus, stationarity is an essential characteristic for data series. Table 2 gives the results of Augmented Dickey Fuller (1981), Phillips- Perron (1992), and Kwiatkowski *et al* (1992) (hereafter ADF, PP, and KPSS tests, respectively) unit root test. Although rejecting the hypothesis of unit root indicates the random walk and suggests the weak form market efficiency and hence of no memory in the series, detailed analysis is essential since the rejection of unit root hypothesis is not compulsory against long memory (see Hassler and Wolter; 1994, Lee and Schmidt; 1996, Limam; 2003 for more details). Appendix D gives econometric explanations of unit root tests.

Table 2. Unit root tests results

		ISE100	ISEIND	ISEFIN	ISESRV	ISETECH
	η_μ	-19.6873(9)*	-18.1313(9)*	-18.2247(10)*	-13.6886(12)*	-11.9298(10)*
ADF	η_τ	-19.6989(9)*	-18.1615(9)*	-18.2368(10)*	-13.7005(12)*	-11.9579(10)*
	η_μ	-63.3631(17)*	-60.4079(18)*	-60.9259(15)*	-51.8287(0)*	-42.8009(5)*
PP	η_τ	-63.3583(17)*	-60.4041(18)*	-60.8887(14)*	-51.8304(1)*	-42.8105(5)*
	η_μ	0.1405(20)	0.1901(20)	0.1508(16)	0.1739(0)	0.1410(5)
KPSS	η_τ	0.0486(20)	0.0270(20)	0.0663(16)	0.1237(0)	0.0509(5)

Note: η_τ and η_μ refer to the test statistics with and without trend, respectively.

Nonlinear structure of the data, such as long memory or chaos, violates the assumptions of normal distribution and particularly the independent and identical distribution (hereafter, IID). Departure from IID hypothesis indicates that stock prices are potentially predictable, that is weak form efficiency. Moreover, Classical unit root tests are incapable to exclude the dependence or systematic patterns that could refer long memory (Limam, 2003). Therefore, it is important to analyzing the randomness and IID distributional properties.

Table 3 gives the results of Brock – Dechert – Scheinkman (hereafter, BDS) test proposed by Brock et al (1996). Consistent with Hsieh's (1991) approach, the distances between two points, ε, are taken 0.5σ, σ, 1.5σ, and 2σ; Additionally, the maximum embedding dimension, *m*, equals six according to the suggestions of Brock et al (1996). The null hypothesis of IID distribution is strongly rejected for all indices. Although reported here, normal and bootstrapped probabilities are lower than 5% significance level. Thus, return series is not distributed independently and identically, suggesting the possibility of predictable behavior.

Table 3. BDS statistics for ISE indices daily returns

e/σ	*m*	ISE100	ISEIND	ISEFIN	ISESRV	ISETECH
0.5	2	0.0105	0.0117	0.0084	0.0129	0.0140
0.5	3	0.0107	0.0128	0.0084	0.0137	0.0158
0.5	4	0.0073	0.0092	0.0057	0.0100	0.0116
0.5	5	0.0043	0.0058	0.0033	0.0062	0.0075
0.5	6	0.0024	0.0035	0.0018	0.0038	0.0044
1	2	0.0235	0.0254	0.0195	0.0254	0.0261
1	3	0.0407	0.0459	0.0339	0.0455	0.0498
1	4	0.0469	0.0539	0.0391	0.0547	0.0610
1	5	0.0465	0.0548	0.0385	0.0560	0.0642
1	6	0.0428	0.0521	0.0351	0.0537	0.0617
1.5	2	0.0233	0.0248	0.0204	0.0230	0.0229
1.5	3	0.0497	0.0540	0.0432	0.0500	0.0521
1.5	4	0.0698	0.0761	0.0607	0.0723	0.0762
1.5	5	0.0847	0.0930	0.0736	0.0892	0.0964
1.5	6	0.0948	0.1053	0.0824	0.1022	0.1104
2	2	0.0166	0.0178	0.0152	0.0156	0.0150
2	3	0.0386	0.0416	0.0347	0.0367	0.0372
2	4	0.0589	0.0636	0.0530	0.0572	0.0586
2	5	0.0782	0.0848	0.0706	0.0764	0.0806
2	6	0.0960	0.1046	0.0870	0.0948	0.1004

Notes: All the BDS statistics are significant at 0.01 level. e/σ and m denote the distance between two points and embedding dimension, respectively.

The non-parametric RUNS test is used to evaluate the randomness of the return series. According to the RUNS test results given in table 4, the null hypothesis of random distribution is rejected for all indices except for ISESRV and ISETECH at the 5% significant level. Too large number of runs suggests the repeated alternating pattern for ISE100, ISEIND, and ISEFIN. We investigate hidden patterns causing the returns to departure from IID and randomness in terms of long memory. Appendix D gives econometric explanations of BDS test.

Table 4. RUNS test statistics for ISE indices daily returns

Indices	Number of runs	Z-statistics	Two-tailed significance
ISE100	2301	4.479776	0.000007
ISEIND	1977	3.632187	0.000281
ISEFIN	2029	2.024751	0.042893
ISESRV	1353	0.134815	0.892758
ISETEC	912	0.466126	0.641125

3.2. Empirical Results

3.2.1. Estimation results of ARFIMA models

There is a vast literature evaluating the performance of parametric and semi parametric long memory tests. Ballie (1996) specifies that semi parametric methods have shortcomings, such as lack of robustness of the R/S statistics in the presence of heteroscedasticity and short memory, or difficulty of calculation and ambiguity about distinguishing between short range dependencies and long range dependencies in modified R/S analysis proposed by Hurst (1951). Agiakloglou, Newbold and Wohar (1992) point out the inefficiency and biasness causing misleading results of the GPH method when data generating process is AR(1) or MA(1) with large positive parameters, denoting that the series is not IID, in moderate samples. Since the ISE indices return series is not distributed independently and identically, the ARFIMA model independent of the information of the underlying distribution is employed to analyze the ISE indices in terms of long memory.

Table 5 gives the results and diagnostics of $ARFIMA(\psi,\xi,\theta)$ model for ISE100. Since the long memory parameter can become biased in view of high AR and MA orders, the best ARFIMA model is selected among all possible combinations under the restrictions of $\psi+\theta\leq 2$ based on minimum Akaike information criteria (hereafter, AIC) consistent with the Cheung's (1993) suggestions and Caporin's findings (2003) that information criteria successfully distinguish the presence of long memory. AIC with the value of -4.24233 selects the $ARFIMA(2,\xi,2)$ model. The significant long memory parameter indicates the presence of long memory in ISE100 index returns. However, diagnostic tests point out some deficiencies about modeling long memory only in return series. The null hypothesis that residuals are normally distributed is strongly rejected by J-B test; moreover, residuals exhibit skewness and excess kurtosis indicating the leptokurtic distribution. Additionally, highly significant ARCH test statistics indicates the existence of ARCH effect in the standardized residuals. Finally, Box-Pierce statistics reject the null hypothesis of IID distribution. Thus, necessity of modeling long memory in volatility in addition to return series is proven (for details, see Kang and Yoon (2007)).

Table 5. ARFIMA models estimation results for ISE100 index

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*
	(0.0008)	(0.0005)	(0.0005)	(0.0005281)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
ψ_1	-	-	-	0.0883*	0.00477	0.0928	0.0793*	0.6216*	-0.9748*
				(0.0240)	(0.1555)	(0.4469)	(0.0268)	(0.1727)	(0.0780)
ψ_2	-	-	-	-	-	-	-0.0130	-0.0579*	-0.7523*
							(0.0174)	(0.0144)	(0.0813)
ξ	0.0744*	0.0234	0.0227	0.0187	0.0231	0.0263	0.0285	0.0650	0.0480*
	(0.0117)	(0.0165)	(0.0225)	(0.0187)	(0.0197)	(0.0297)	(0.0228)	(0.0416)	(0.0135)
θ_1	-	0.0841*	0.0849*	-	0.0797	-0.0119	-	-0.5788*	1.0284*
		(0.0211)	(0.0272)		(0.1452)	(0.4667)		(0.1905)	(0.0709)
θ_2	-	-	0.0008	-	-	-0.0110	-	-	0.7940*
			(0.0191)			(0.0582)			(0.0736)
$\ln(L)$	10415.6609	10422.9116	10422.9126	10422.7606	10422.9121	10422.9272	10423.0418	10423.8765	10430.394
AIC	-4.23796	-4.24050	-4.24009	-4.24044	-4.24009	-4.23969	-4.24015	-4.24008	-4.24233
Skewness	-0.0373	-0.0527	-0.0528	-0.0523	-0.0527	-0.0527	-0.0531	-0.0560	-0.0444
Excess Kurtosis	3.2566	3.2456	3.2444	3.2353	3.2450	3.2501	3.2528	3.2468	3.0936
J-B	1075.2*	1068.1*	1067.5*	1063.1*	1067.8*	1070.4*	1071.7*	1068.3*	994.66*
$Q(20)$	50.413*	36.867*	36.895*	37.392*	36.880*	36.723*	36.435*	33.522*	23.028**
ARCH(4)	154.70*	156.60*	156.56*	156.50*	156.56*	156.54*	156.61*	156.74*	154.72*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

Table 6 summarizes the estimation and diagnostic test results for ISEIND index. The $ARFIMA(2,\xi,2)$ model is selected via the minimum AIC value of -4.39365. Similar to ISE100, significant fractional integration parameter indicates long memory denoting hyperbolically, rather than exponentially, autocorrelation coefficient declining. Diagnostic tests indicates that besides the long memory in return series, analyzing the long memory in ISEIND index volatility is more suitable for capturing long memory characteristics.

Long memory is detected in ISEFIN return series in estimated $ARFIMA(0,\xi,0)$ model selected based on minimum AIC value of -4.05371. As shown in Table 7, ISEFIN return series have long memory proven by significant fractional integration parameter. However, diagnostic tests reveal that analyzing long memory in volatility, along with in return, is more suitable for capturing the existence of long memory property.

Table 8 summarizes the estimation and diagnostic test results for ISESRV index. The $ARFIMA(0,\xi,0)$ model has been retained based on the minimum AIC value of -4.27193. Surprisingly, the fractional integration parameter of 0.0112 is statistically insignificant indicating short memory in index returns. ARCH test result indicating ARCH effect, and other diagnostic tests suggesting the departure from normality put pressure on investigating long memory in volatility. Since the ISESRV index have short memory, data generating process of $ARMA(\psi,\theta)$ is more convenient than *ARFIMA* models. Table 9 gives the results of *ARMA* process. The $ARMA(0,0)$ model has been retained for ISESRV index. Like in *ARFIMA* model, the diagnostic tests of $ARMA(0,0)$ indicates the necessity of analyzing the volatility of index in terms of long memory.

Table 6. Estimation results of ARFIMA models for ISEIND index

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	0.0017* (0.0006)	0.0017* (0.0005)	0.0017* (0.0006)	0.0017* (0.0005)	0.0017* (0.0005)	0.0017* (0.0000)	0.0017* (0.0006)	0.0017* (0.0006)	0.0017* (0.0006)
ψ_1	-	-	-	0.0554* (0.0258)	-0.0714 (0.2343)	-0.0919 (0.5357)	0.0419 (0.0296)	0.3992 (0.5038)	-1.0328* (0.0608)
ψ_2	-	-	-	-	-	-	-0.0177 (0.0194)	-0.0359** (0.0211)	-0.8397* (0.0476)
ξ	0.0549* (0.0125)	0.0210 (0.0187)	0.0312 (0.0260)	0.0200 (0.0202)	0.0238 (0.0201)	0.0244 (0.0315)	0.0341 (0.0254)	0.0486 (0.0403)	0.0348* (0.0135)
θ_1	-	0.0554* (0.0240)	0.0444 (0.0308)	-	0.1240 (0.2250)	0.1437 (0.5585)	-	-0.3718 (0.5273)	1.0750* (0.0539)
θ_2	-	-	-0.0120 (0.02051)	-	-	0.0002 (0.05606)	-	-	0.8780* (0.04226)
$\ln(L)$	9191.91	9194.41	9194.59	9194.30	9194.48	9194.48	9194.71	9194.93	9205.10
AIC	-4.38926	-4.38998	-4.38958	-4.38992	-4.38953	-4.38905	-4.38964	-4.38926	-4.39365
Skewness	-0.0823	-0.0942	-0.0935	-0.0938	-0.0940	-0.0940	-0.0938	-0.0952	-0.0895
Excess Kurtosis	4.2331	4.2204	4.2343	4.2176	4.2253	4.2265	4.2355	4.2264	4.0061
J-B	1341.2*	1332.8*	1339.3*	1331.6*	1335.1*	1335.7*	1339.8*	1335.3*	1237.2*
$Q(20)$	40.841*	37.196*	36.187*	37.526*	36.848*	36.796*	35.827*	34.922*	19.043
ARCH(4)	183.27*	182.45*	182.12*	182.55*	182.31*	182.25*	182.01*	181.90*	180.83*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

Table 7. Estimation results of ARFIMA models for ISEFIN index

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	0.0019* (0.0008)	0.0019* (0.0000)	0.0019* (0.0006)	0.0019* (0.0007)	0.0019* (0.0007)	0.0019* (0.0006)	0.0019* (0.0006)	0.0019* (0.0006)	0.0019* (0.0007)
ψ_1	-	-	-	0.0273 (0.0255)	0.1569 (0.4740)	-0.6623* (0.3067)	0.0377 (0.0297)	-0.2389 (0.6976)	-0.2169 (0.6013)
ψ_2	-	-	-	-	-	-	0.0136 (0.0195)	0.0282 (0.0423)	-0.3034 (0.9748)
ξ	0.05317* (0.0123)	0.05317* (0.0199)	0.0253 (0.0240)	0.0361** (0.0200)	0.0317 (0.0280)	0.0275 (0.0206)	0.0254 (0.0253)	0.0245 (0.0231)	0.0365 (0.0389)
θ_1	-	-0.0001 (0.0249)	0.0382 (0.0287)	-	-0.1246 (0.4559)	0.6986* (0.3017)	-	0.2777 (0.6993)	0.2450 (0.5963)
θ_2	-	-	0.0154 (0.0197)	-	-	0.0411** (0.0231)	-	-	0.3125 (0.9331)
$\ln(L)$	8489.45	8489.45	8490.31	8490.03	8490.13	8491.01	8490.28	8490.53	8490.36
AIC	-4.05371	-4.05323	-4.05317	-4.05351	-4.05308	-4.05302	-4.05315	-4.05280	-4.05224
Skewness	-0.0143	-0.0144	-0.0186	-0.0185	-0.0186	-0.0172	-0.0184	-0.0185	-0.0193
Excess Kurtosis	3.1652	3.1651	3.1463	3.1659	3.1613	3.1208	3.1481	3.1362	3.1533
J-B	880.75*	880.72*	872.74*	880.92*	879.00*	862.17*	873.49*	868.53*	875.64*
$Q(20)$	40.677*	40.683*	39.769*	39.979*	39.873*	38.970*	39.765*	39.634*	40.079*
ARCH(4)	110.26*	110.23*	110.85*	111.00*	110.98*	110.66*	110.83*	110.71*	110.83*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

Table 8. Estimation results of ARFIMA models for ISESRV index

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*
	(0.0006)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
ψ_1	-	-	-	-0.0256	-0.7469*	-0.6587*	-0.0009	-0.6318*	-0.5798*
				(0.03108)	(0.1676)	(0.2137)	(0.0376)	(0.2371)	(0.4896)
ψ_2	-	-	-	-	-	-	0.0299	0.0266	0.0528
							(0.0251)	(0.0332)	(0.4640)
ξ	0.0112	0.0261	0.0045	0.0270	0.0245	0.0083	0.0027	0.0088	0.0077
	(0.0150)	(0.0249)	(0.0301)	(0.0246)	(0.0175)	(0.0265)	(0.0320)	(0.0272)	(0.0278)
θ_1	-	-0.02377	-0.0020	-	0.7195	0.6538*	-	0.6259*	0.5749
		(0.0309)	(0.0358)		(0.1766)	(0.2088)		(0.2284)	(0.4901)
θ_2	-	-	0.0267	-	-	0.0273	-	-	-0.0241
			(0.0232)			(0.0324)			(0.4633)
$\ln(L)$	5763.70	5764.01	5764.66	5764.04	5765.61	5765.92	5764.75	5765.90	5765.88
AIC	-4.27193	-4.27142	-4.27116	-4.27142	-4.27186	-4.27136	-4.27123	-4.27134	-4.27059
Skewness	0.0020	0.0206	0.0185	0.0223	0.0340	0.0206	0.0197	0.0214	0.0213
Excess Kurtosis	5.5762	5.5922	5.5221	5.5923	5.4808	5.4292	5.5149	5.4328	5.4343
J-B	1286.3*	1291.0*	1269.0*	1290.9*	1255.3*	1239.8*	1266.7*	1240.9*	1241.4*
$Q(20)$	35.454*	34.864*	34.292*	34.824*	32.607*	32.325*	34.238*	32.352*	32.425*
ARCH(4)	97.538*	96.779*	96.395*	96.699*	96.336*	96.628*	96.318*	96.605*	96.528*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

Table 9. ARMA models estimation results for ISESRV index

	(0,0)	(0,1)	(0,2)	(1,0)	(1,1)	(1,2)	(2,0)	(2,1)	(2,2)
μ	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
ψ_1	-	-	-	0.0019	0.0043	-0.6413*	0.0019	-0.6045*	-0.4476
				(0.01926)	(0.6535)	(0.2058)	(0.01925)	(0.2216)	(1.156)
ψ_2	-	-	-	-	-	-	0.0313	0.0348**	0.1676
							(0.01925)	(0.02039)	(1.021)
ξ	-	-	-	-	-	-	-	-	-
θ_1	-	0.0018	0.0025	-	-0.0022*	0.6446*	-	0.6075*	0.4499
		(0.0187)	(0.0193)		(0.6340)	(0.2061)		(0.2212)	(1.162)
θ_2	-	-	0.0288	-	-	0.0350**	-	-	-0.1313
			(0.0184)			(0.0203)			(1.014)
$\ln(L)$	5763.42	5763.43	5764.65	5763.43	5763.43	5765.88	5764.75	5765.85	5765.81
AIC	-4.27247	-4.27173	-4.27190	-4.27173	-4.27099	-4.27206	-4.27197	-4.27204	-4.27127
Skewness	-0.0057	-0.0064	0.0153	-0.0064	-0.0065	0.0132	0.0180	0.0140	0.0183
Excess Kurtosis	5.5621	5.5625	5.5127	5.5626	5.5626	5.4125	5.5098	5.4159	5.4291
J-B	1281.9*	1282.0*	1266.2*	1282.0*	1282.0*	1234.8*	1265.2*	1235.9*	1239.9*
$Q(20)$	36.004*	35.991*	34.364*	35.990*	35.990*	32.471*	34.279*	32.512*	32.620*
ARCH(4)	97.476*	97.503*	96.480*	97.507*	97.477*	96.807*	96.379*	96.781*	96.604*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

AIC value of -4.27445 selects the $ARFIMA(2,\xi,2)$ model for ISETECH index. Table 10 reports fractional differencing parameters for various $ARFIMA$ models and diagnostic tests for daily ISETECH returns. Interestingly, insignificant fractional differencing parameter denoting ξ equals to zero indicates the presence of short memory pattern, not long memory in returns. Thus, modeling the daily ISETECH returns via data generating process of ARMA, rather than ARFIMA, is more appropriate. Similar to other indices discussed above, the diagnostics indicating ARCH effects, significant skewness and kurtosis, and not IID distribution considering the long memory in volatility is required in terms of modeling long memory. The data generating process results, given in table 11, indicates that the best model is $ARMA(2,2)$ via the minimum AIC value of -4.27523. The diagnostic test very close $ARFIMA$ model suggests that investigating long memory is necessary.

The long memory in returns implies that stock prices follow a predictable behavior, which is inconsistent with the efficient market hypothesis. Hence we conclude that ISE100, ISEFIN, and ISEIND indices putrefy efficient market hypothesis. These indices consists the effects of news and shocks occurring in the past; Thus speculative earnings can be gained via predicting price by using historic prices. This result supports the findings of recent studies, which claim that long memory property is generally a characteristic of emerging rather than developed stock markets.

Table 10. Estimation results of ARFIMA models for ISETEC index

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	-0.0001	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0008)	(0.0009)	(0.0007)	(0.0009)	(0.0005)	(0.0006)	(0.0007)	(0.0006)	(0.0006)
ψ_1	-	-	-	-0.0462	0.7884*	0.3550	-0.0006	0.3012	1.1793*
				(0.0383)	(0.1104)	(0.2949)	(0.0499)	(0.3246)	(0.0512)
ψ_2	-	-	-	-	-	-	0.0486	0.0551*	-0.8724*
							(0.0325)	(0.0279)	(0.0545)
ξ	0.0180	0.0451	0.0092	0.0477	-0.0832	-0.0205	0.0033	-0.0205	-0.0162
	(0.0183)	(0.0317)	(0.0369)	(0.0310)	(0.0814)	(0.0547)	(0.0435)	(0.0586)	(0.0217)
θ_1	-	-0.0413	-0.0080	-	-0.7005*	-0.3330	-	-0.2786	-1.1548*
		(0.0382)	(0.0427)		(0.1663)	(0.2651)		(0.2950)	(0.0489)
θ_2	-	-	0.0454	-	-	0.0553*	-	-	0.8982*
			(0.0285)			(0.0264)			(0.0477)
$\ln(L)$	3932.51	3933.11	3934.35	3933.21	3933.70	3934.71	3934.35	3934.63	3943.77
AIC	-4.26657	-4.26614	-4.26639	-4.26624	-4.26569	-4.26570	-4.26639	-4.26561	-4.27445
Skewness	-0.0486	-0.0085	-0.0050	-0.0020	-0.0349	-0.0170	-0.0085	-0.0170	-0.0610
Excess Kurtosis	8.2077	8.2114	8.1075	8.2085	8.2713	8.1232	8.0969	8.1228	7.8350
J-B	1472.6*	1475.2*	1451.5*	1474.6*	1488.1*	1454.9*	1449.0*	1454.8*	1386.5*
$Q(20)$	42.290*	41.114*	38.928*	40.956*	44.164*	39.945*	39.063*	40.004*	24.565**
ARCH(4)	83.887*	84.495*	87.051*	84.695*	83.841*	86.736*	87.227*	86.756*	84.235*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

Table 11. ARMA models estimation results for ISETECH index

	(0,0)	(0,1)	(0,2)	(1,0)	(1,1)	(1,2)	(2,0)	(2,1)	(2,2)
μ	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)	-0.0001 (0.0007)
ψ_1	-	-	-	0.0028 (0.0233)	0.0046 (0.4779)	0.2843 (0.2842)	0.0027 (0.0233)	0.2338 (0.3110)	1.1798* (0.0465)
ψ_2	-	-	-	-	-	-	0.0502* (0.0233)	0.0505* (0.0238)	-0.8844* (0.0505)
ξ	-	-	-	-	-	-	-	-	-
θ_1	-	0.0026 (0.0222)	0.0009 (0.0233)	-	-0.0015 (0.4557)	-0.2827 (0.2838)	-	-0.2318 (0.3110)	-1.1610* (0.0434)
θ_2	-	-	0.0496* (0.0230)	-	-	0.0516* (0.0239)	-	-	0.9106* (0.0437)
$\ln(L)$	3932.01	3932.02	3934.32	3932.02	3932.02	3934.64	3934.35	3934.56	3943.49
AIC	-4.26711	-4.26603	-4.26744	-4.26603	-4.26495	-4.26670	-4.26748	-4.26662	-4.27523
Skewness	-0.0841	-0.0833	-0.0151	-0.0832	-0.0832	-0.0027	-0.0116	-0.0034	-0.0349
Excess Kurtosis	8.1477	8.1532	8.0864	8.1537	8.1541	8.1407	8.0907	8.1367	7.9111
J-B	1455.3*	1456.6*	1446.5*	1456.8*	1456.8*	1459.1*	1447.6*	1458.2*	1405.7*
$Q(20)$	43.580*	43.531*	39.014*	1456.8*	43.523*	39.502*	39.103*	39.529*	24.713**
ARCH(4)	83.287*	83.248*	87.183*	83.249*	83.205*	86.755*	87.307*	86.801*	84.538*

Notes : QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria.
The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4.
The skewness and kurtosis are also based on standardized residuals.* and ** indicate significance levels at the 5% and 10%, respectively.

3.2.2. Estimation results of FI(E)GARCH models

The performance of the mostly used symmetric short memory models of GARCH, IGARCH; asymmetric short memory models of EGARCH, GJR-GARCH, APARCH; as well as symmetric long memory model of FIGARCH; asymmetric long memory models of FIEGARCH and FIAPARCH models are evaluated in terms of modeling volatility process in ISE indices. The estimation results of EGARCH, GJR-GARCH, and FIEGARCH are not reported here since the asymmetry parameters are statistically insignificant indicating the absence of asymmetry or the leverage effect in ISE. Thus, modeling volatility of ISE based on symmetric models is a more appropriate approach in terms of capturing volatility.

Table 12 summarizes the GARCH (1,1), IGARCH (1,1), and FIGARCH (1,1) specifications under the assumption of normal distribution. Standardized residuals having no arch effect indicate that variance equation is specified correctly. The ARCH LM test statistics based on GARCH model rejects the null of no arch effect, which indicates the inefficiency of capturing volatility. Moreover, the fact that the sum of arch and garch parameters being approximately 0.98, which is close to the unity and means volatility is highly persistent, suggests the IGARCH model. The estimation results parameters of the GARCH and IGARCH model are very similar. Like GARCH model, IGARCH model is incapable in terms of modeling volatility based on ARCH LM test. Moreover, RBD test statistic proposed by Tse (2001) rejects the null hypothesis of well specified conditional variance equation for GARCH and IGARCH models, thus, these models are not preferred for modeling volatility persistence. However, FIGARCH is a more appropriate model based on ARCH LM and RBD tests for ISE100 daily returns. Most importantly, significant fractionally integration parameter, d, of FIGARCH model indicates the superiority of the FIGARCH model and denotes the presence of long memory in ISE100 daily returns. Significant J-B statistics, as well as skewness and kurtosis, violates the null hypothesis of normal distribution. Additionally, the rejection of the null hypothesis of uniformity between empirical and theoretical distributions based on Pearson goodness-of-fit test suggests the utilization of student t distribution, rather than normal distribution. Appendix D gives econometric explanations of ARCH LM, Pearson, and RBD tests. Also Appendix E gives econometric explanations of model densities.

Table 12. Estimation results of FIGARCH models for daily Index returns of ISE100

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.0016* (0.0003)	0.0016* (0.0003)	0.0016* (0.0003)
ω	0.2172* (0.0439)	0.1496* (0.0276)	0.3512* (0.1018)
α_1	0.1407* (0.0141)	0.1510* (0.0145)	0.1820** (0.0978)
β_1	0.8413* (0.015866)	0.8492	0.3729* (0.1106)
d	-	1	0.3715* (0.0379)
$\ln(L)$	10939.953	10935.855	10978.983
AIC	-4.45094	-4.44968	-4.46642
SIC	-4.44565	-4.44571	-4.45980
Skewness	-0.2037*	-0.2049*	-0.1894*
Excess kurosis	1.7357*	1.7629*	1.5668*
J-B	650.87*	670.70*	532.03*
ARCH(4)	2.7484*	2.6611*	1.0757
RBD(4)	10.9353*	11.0954*	3.8694
P(60)	141.3846*	163.6557*	106.3175*

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

The FIGARCH model outperforms the GARCH and IGARCH model based on estimation results displayed in Table 13 and table 14 for ISEIND and ISEFIN index returns, respectively. The ARCH LM and RBD test statistics are insignificant indicating the accuracy of well specified variance equation, only for the FIGARCH model. Besides, significant fractional integration parameter proves the long memory pattern in ISEIND index returns; as a consequence, traditional short memory models are incapable for modeling volatility. Diagnostic statistics implies the deficiency of the normality assumption. Pearson and J-B statistics strongly rejects the null hypothesis of normal distribution; also highly significant skewness and kurtosis imply the presence of leptokurtic distribution.

Table 13. Estimation results of FIGARCH models for daily Index returns of ISEIND

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.0016*	0.0016*	0.0017*
	(0.0003)	(0.0003)	(0.0003)
ω	0.0954*	0.0831*	0.1944*
	(0.0217)	(0.0167)	(0.0746)
α_1	0.1255*	0.1300*	0.2683*
	(0.0129)	(0.0125)	(0.1216)
β_1	0.8692*	0.8702	0.4396*
	(0.0128)		(0.1313)
d	-	1	0.3583*
			(0.0377)
$\ln(L)$	9782.98	9782.41	9823.71
AIC	-4.67112	-4.67132	-4.69009
SIC	-4.66506	-4.66678	-4.68252
Skewness	-0.3431*	-0.3469*	-0.3300*
Excess kurosis	1.9916*	1.9981*	1.8586*
J-B	774.12*	780.48*	678.67*
ARCH(4)	3.2632*	3.1459*	0.8362
RBD(4)	12.2700*	11.6053*	7.3181
P(60)	142.0709*	146.0834*	91.1705*

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

Table 15 summarizes the FIGARCH model estimation results for ISESRV index. ISESRV index return volatilities exhibit considerably analogous pattern with ISE100, ISEIND. For ISEFIN and ISESRV index return volatilities, FIGARCH outclasses the other short memory models in terms of modeling volatility, and ascertains the existence of long memory in return volatility. Moreover, drawbacks in normal distribution assumption are evidenced via J-B and Pearson tests, along with skewness and excess kurtosis, like other indices discussed above.

Table 14. Estimation results of FIGARCH models for daily Index returns of ISEFIN

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.001722*	0.001745*	0.001697*
	(0.0004)	(0.0004)	(0.0004)
ω	0.1611*	0.1020*	0.3846*
	(0.0393)	(0.0236)	(0.1219)
α_1	0.0973*	0.1036*	0.2188*
	(0.0115)	(0.0118)	(0.0837)
β_1	0.8902*	0.8966	0.4421*
	(0.0131)		(0.0971)
d	-	1	0.3658*
			(0.0403)
$\ln(L)$	8904.997	8901.150	8930.411
AIC	-4.251730	-4.250370	-4.263392
SIC	-4.245674	-4.245828	-4.255821
Skewness	-0.1523*	-0.1546*	-0.1296*
Excess kurosis	1.6302 *	1.6328*	1.4149*
J-B	479.78*	481.81*	360.95*
ARCH(4)	3.2547*	2.8532*	1.5116
RBD(4)	12.550*	11.1075*	5.6046
P(60)	108.4239*	116.7640*	92.2596*

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.

* denotes the significance levels at the 5

Table 15. Estimation results of FIGARCH models for daily Index returns of ISESRV

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.0017*	0.0018*	0.0018*
	(0.0004)	(0.0004)	(0.0004)
ω	0.2058*	0.1858*	0.6918*
	(0.0420)	(0.0348)	(0.1712)
α_1	0.1717*	0.1828*	-0.2724**
	(0.0209)	(0.0190)	(0.1607)
β_1	0.8187*	0.8174	-0.1614
	(0.0192)		(0.1681)
d	-	1	0.3110*
			(0.0324)
$\ln(L)$	6147.376	6146.826	6174.761
AIC	-4.55571	-4.55605	-4.57528
SIC	-4.546960	-4.549482	-4.564339
Skewness	0.1088*	0.1143*	0.13610*
Excess kurosis	3.9516*	4.0064*	3.8443 *
J-B	1760.1*	1809.6*	1669.1*
ARCH(4)	2.1981**	2.1308**	1.0705
RBD(4)	8.7758**	8.6374**	4.0913
P(60)	132.0768*	132.4772*	107.0267*

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

Finally, Table 16 reports the short and long memory model estimation results of daily ISETECH index returns. Although ARCH and RBD tests accept the null of well specified variance equation, significant fractional integration parameter, d, indicates the existence of long memory and the superiority of the FIGARCH model. Like other indices, the assumption of normal distribution is failed to accept by J-B and Pearson test. Moreover, significant skewness and excess kurtosis indicate the distribution of the ISETECH index is leptokurtic suggesting student-t or skewed t distribution is more appropriate. Consequently, ISE has long memory characteristics consistent with previous research results indicating developing countries have long memory pattern.

Table 16. Estimation results of FIGARCH models for daily Index returns of ISETECH

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.0007	0.0007	0.0009**
	(0.0005)	(0.0005)	(0.0005)
ω	0.3751*	0.2631*	1.5051*
	(0.0798)	(0.0641)	(0.3291)
α_1	0.1232*	0.1645*	-0.5314*
	(0.0202)	(0.0276)	(0.1616)
β_1	0.8306*	0.8357	-0.4334*
	(0.0260)		(0.1733)
d	-	1	0.2302*
			(0.0296)
$\ln(L)$	4187.52	4176.62	4208.78
AIC	-4.54237	-4.53162	-4.56436
SIC	-4.53038	-4.52263	-4.54938
Skewness	0.1027**	0.2585*	0.2446*
Excess kurtosis	11.723*	15.959*	11.817*
J-B	10551*	19567*	10735*
ARCH(4)	0.5029	0.2731	0.3733
RBD(4)	2.0043	1.3208	1.4978
P(60)	172.9837*	186.9251*	151.3550*

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

3.2.3. Estimation results of ARFIMA-FIGARCH models

Thus far, long memory in conditional mean and in conditional variance are analyzed separately; however, since the previous literature reveals the occurrence of long memory in both conditional mean and in conditional variance simultaneously, investigating dual long memory is more feasible for capturing the memory characteristics. Moreover, it is worthwhile to investigate the efficiency of the various distributions because the invalidity of the normal distribution assumption is proven by diagnostic checking and Pearson test. Thus, ARFIMA-FIGARCH model with the student-t and skewed student- t distributions is used to capture dual long memory.

Table 17 summarizes the ARFIMA-FIGARCH estimation results of ISE100 index under the normal, student-t, and skewed student-t distributions. The null hypothesis of correct distribution is accepted for student-t and skewed student-t distributions. Whereas, statistically insignificant degree of asymmetry in skewed student-t distribution implies the superiority of student-t distribution. The significant fractionally integration parameters in conditional mean and variance, denoting ξ and d respectively, indicate the existence of dual long memory in returns and volatility of ISE.

Table 17. Estimation results of ARFIMA-FIGARCH models for daily index returns of ISE100

	Normal	Student-*t*	Skewed Student-*t*
μ	0.0016*	0.0019*	0.0019*
	(0.0005)	(0.0005)	(0.0005)
ψ_1	-0.3917	-0.1377	-0.1374
	(0.3418)	(0.3519)	(0.3519)
ψ_2	-0.4184	-0.3309	-0.3309
	(0.2590)	(0.2058)	(0.2058)
ξ	0.0508*	0.0608*	0.0608*
	(0.0191)	(0.0208)	(0.0208)
θ_1	0.4529	0.1780	0.1796
	(0.3356)	(0.3638)	(0.3638)
θ_2	0.4215	0.3035	0.3034
	(0.2667)	(0.2086)	(0.2085)
ω	0.4197*	0.4377*	0.4378*
	(0.1339)	(0.1517)	(0.1519)
α_1	0.0811	0.0438	0.0436
	(0.1321)	(0.1519)	(0.1521)
β_1	0.2708**	0.2364	0.2362
	(0.1499)	(0.1736)	(0.1738)
d	0.3602*	0.3754*	0.3754*
	(0.0375)	(0.0450)	(0.0450)
v	-	-	8.1566*
			(0.8158)
ln(γ)	-	-	-0.0005
			(0.0212)
$\ln(L)$	11007.87	11090.74	11090.74
AIC	-4.47614	-4.50946	-4.50905
ARCH(4)	1.0157	1.0421	1.0420
RBD(4)	3.7051	2.8461	2.8431
P(60)	107.5140*	49.2967	48.7839

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.
ln(γ) denotes asymmetry parameter. *v* is the tail parameter.

Like ISE100 indices, ARFIMA-FIGARCH models capture the dual long memory in mean and in volatility for ISEIND returns based on significant fractionally integration parameters summarized in Table 18. Pearson test statistics is failed to accept the null hypothesis of correct distribution for normal distribution, which indicates the inefficiency of the Gaussian distribution, for ISEIND returns. Moreover, degree of asymmetry parameter is statistically significant implying the superiority of skewed student-t distribution. Negative degree of asymmetry indicates the left skewed density for ISEIND series. Consequently, ISEIND index has long memory both in return and volatility based on the ARFIMA-FIGARCH model.

Table 18. Estimation results of ARFIMA-FIGARCH models for daily index returns of ISEIND

	Normal	Student-*t*	Skewed Student-*t*
μ	0.0018* (0.0004)	0.0022* (0.0004)	0.0019* (0.0004)
ψ_1	-0.9517* (0.0860)	-0.6902* (0.1701)	-0.6637* (0.1596)
ψ_2	-0.7151* (0.0687)	-0.5835* (0.1408)	-0.5786* (0.1555)
ξ	0.0344* (0.01505)	0.0360* (0.0155)	0.0337* (0.0157)
θ_1	0.9780* (0.0803)	0.7165* (0.1721)	0.6902* (0.1624)
θ_2	0.7405* (0.0696)	0.5892* (0.1422)	0.5821* (0.1541)
ω	0.2420* (0.1065)	0.2186** (0.1149)	0.2199** (0.1207)
α_1	0.1850 (0.1752)	0.1656 (0.2078)	0.1517 (0.2244)
β_1	0.3493** (0.1900)	0.3345 (0.2244)	0.3184 (0.2429)
d	0.3441* (0.0375)	0.3463* (0.0434)	0.3451* (0.0439)
v	-	-	7.4509* (0.7268)
ln(γ)	-	-	-0.0422** (0.0224)
$\ln(L)$	9839.61	9931.16	9932.93
AIC	-4.69530	-4.73855	-4.73892
ARCH(4)	1.0043	1.2636	1.2826
RBD(4)	4.1662	5.1994	5.1513
P(60)	120.3752*	70.5639	71.1084

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.
ln(γ) denotes asymmetry parameter. *v* is the tail parameter.

Table 19 reports the estimation results of ARFIMA-FIGARCH model for ISEFIN index. The null of correct distribution is accepted only for student-t distribution, additionally, degree of asymmetry in skewed student-t distribution is statistically insignificant, which indicates the invalidity of skewed distribution. Thus, student-t distribution outperforms the normal and skewed student-t distributions. ARFIMA(*0*, ξ,*0*)-FIGARCH(1,d,1) model under student-t distribution captures the dual long memory in ISEFIN index.

Table 19. Estimation results of ARFIMA-FIGARCH models for daily index returns of ISEFIN

	Normal	Student-*t*	Skewed Student-*t*
μ	0.0017* (0.0006)	0.0018* (0.0006)	0.0020* (0.0006)
ψ_1	-	-	-
ψ_2	-	-	-
ξ	0.0552* (0.0134)	0.0506* (0.0130)	0.0510* (0.0130)
θ_1	-	-	-
θ_2	-	-	-
ω	0.3950* (0.1252)	0.3827* (0.1368)	0.3801* (0.1359)
α_1	0.1997* (0.0851)	0.2180* (0.0947)	0.2185* (0.0936)
β_1	0.4274* (0.0997)	0.4545* (0.1130)	0.4572* (0.1119)
d	0.3660* (0.0404)	0.3911* (0.0538)	0.3917* (0.0539)
v	-	-	8.1718* (0.9186)
ln(γ)	-	-	0.0203 (0.0222)
$\ln(L)$	8939.47	9003.19	9003.61
AIC	-4.26724	-4.29720	-4.29692
ARCH(4)	1.4444	1.3626	1.3741
RBD(4)	5.4024	6.9155	4.7236
P(60)	118.7129*	72.8280	73.6305**

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.
ln(γ) denotes asymmetry parameter. *v* is the tail parameter.

Although long memory is evidenced only in volatility for ISESRV and ISETECH returns based on FIGARCH estimation results, assumption of normality is rejected via diagnostic checking and Pearson test. Thus, ARMA-FIGARCH model with various distributions is used for detailed memory investigation. Table 20 and 21 exhibit the estimation results of ARFIMA(*0*,*0*)-FIGARCH(1,d,1) and ARFIMA(2,*2*)-

FIGARCH(1,d,1) model under the normal, student-t, and skewed student-t distributions for ISESRV and ISETECH index, respectively. Pearson test statistics rejects the normal distributions as a correct distribution; moreover asymmetry degree of skewed student-t distribution is statistically insignificant for both indices. Thus, ARFIMA(*0,0*)-FIGARCH(1,d,1) and ARFIMA(2,*2*)-FIGARCH(1,d,1) with student-t distribution outperforms and proves the long memory in conditional volatility of ISESRV and ISETECH indices, respectively. Appendix E gives econometric explanations of model densities.

Table 20 Estimation results of ARMA-FIGARCH models for daily index returns of ISESRV

	Normal	Student-*t*	Skewed Student-*t*
μ	0.0018* (0.0004)	0.001481* (0.0004)	0.001608* (0.0004)
ψ_1	-	-	-
ψ_2	-	-	-
ξ	-	-	-
θ_1	-	-	-
θ_2	-	-	-
ω	0.6918* (0.1712)	0.4654** (0.2374)	0.4803* (0.2320)
α_1	-0.2724** (0.1607)	-0.1287 (0.3166)	-0.1436 (0.2987)
β_1	-0.1614 (0.1681)	-0.0060 (0.3318)	-0.0233 (0.3128)
d	0.3110* (0.0324)	0.2896* (0.0383)	0.2889* (0.0375)
v	-	-	6.0404* (0.5910)
ln(γ)	-	-	0.0269 (0.0264)
$\ln(L)$	6174.761	6281.690	6282.208
AIC	-4.575277	-4.653830	-4.653473
ARCH(4)	1.0705	1.5923	1.5591
RBD(4)	4.0913	6.8966	6.7365
P(60)	107.0267*	50.5195	53.6785

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells. * denotes the significance levels at the 5%. ln(γ) denotes asymmetry parameter. *v* is the tail parameter.

Table 21 Estimation results of ARMA-FIGARCH models for daily index returns of ISETECH

	Normal	Student-*t*	Skewed Student-*t*
μ	0.0009 (0.0006)	0.0010* (0.0004)	0.0008** (0.0005)
ψ_1	0.0549 (0.2262)	-0.5807* (0.0764)	-0.5833* (0.0754)
ψ_2	0.2196 (0.2756)	-0.7486* (0.0829)	-0.7556* (0.0796)
ξ	-	-	-
θ_1	-0.0159 (0.2290)	0.5775* (0.0757)	0.5776* (0.0743)
θ_2	-0.1829 (0.2760)	0.7627* (0.0821)	0.7691* (0.0787)
ω	1.4874* (0.3274)	0.7740* (0.3259)	0.7672* (0.3286)
α_1	-0.5361* (0.1581)	-0.6055* (0.1908)	-0.6010* (0.1986)
β_1	-0.4384* (0.1710)	-0.5048* (0.2178)	-0.5011* (0.2260)
d	0.2291* (0.0301)	0.2624* (0.0385)	0.2592* (0.0384)
v	-	-	5.3132* (0.5492)
ln(γ)	-	-	-0.0435 (0.0338)
$\ln(L)$	4213.292	4356.233	4357.065
AIC	-4.5649	-4.7190	-4.7189
ARCH(4)	0.4561	0.1895	0.1882
RBD(4)	1.8383	0.63932	0.65037
P(60)	122.4951*	64.9707	59.2378

ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.
ln(γ) denotes asymmetry parameter. *v* is the tail parameter.

3.3. Volatility Breaks and Persistence analyses results

In this section the effects of multiple unknown structural breaks on long memory in ISE is investigated. The dummies, indicating break dates detected ICSS procedure, are introduced to the GARCH (1,1) model for predicting change in volatility persistence. Appendix C gives econometric explanations of ICSS procedure. Table 22 exhibits appropriate ARMA-GARCH(1,1) model estimation results for ISE indices. Then, ICSS algorithm is implemented to the residuals taken from mean equation of ARMA-GARCH (1,1) model for each index. Table 23 summarizes the break dates under the normal distribution assumption. Appendix F exhibits break dates under the student-t distribution assumption.

A literature proves that occasional breaks, switching regimes, and structural changes have significant effect on generating long memory characteristics. Hyung et al (2006) and Granger et al (2004) examine S&P 500 index and find that occasional breaks could be responsible for evidence of long memory. Diebold and Inoue (2001) perform Monte Carlo analysis and find that the presence of regime switching is capable of producing the long memory property. Mikosch and Starica (2000) prove that structural changes may cause long memory in S&P index.

Lamoureux and Lastrapes (1990) reveal that volatility persistence of shocks is reduced when breaks are introduced to GARCH model. Decline in volatility indicates that occasional breaks could cause long memory. Since market participants' respond to information flow vary, the effect of breaks on persistence, rather than events correlated with break dates, is investigated. Malik and Hassan (2004) states that, break dates varying across indices, indicates each sector have sector-specific factors affecting break dates. Also, rate of information flow and time which is different in each market may cause market participants to respond to information at different times. Moreover, spillover effects within sectors may lead to varying break dates across sector indices.

Engle and Ito and Lin (1990) prove significant evidence in favor of "meteor shower" hypothesis, that effect of information in one market (sector) spread out to other markets (sectors) causing volatility transmission. Thus, evidence leading a break in one market will be transmitted to another market and will lead a break point in that market with time delay. Fleming and Kirby and Ostdiek(1998) state that information, thus volatility, spillovers are strongly caused by common information, such as news about inflation, and cross-market hedging strategies. Hence, The ICSS algorithm is used to examine whether or ISE indices are more sensitive to the major global economic and political events than to local factors, instead of identifying the main causes of the structural breaks in volatility. Our main focus is to investigate the impact of these breakpoints on the persistence in volatility.

Table 22. ARMA-GARCH(1,1) model results for ISE indices

	ISE100		ISESRV		ISEFIN		ISEIND		ISETECH	
	Normal	Student-*t*	Normal	Student-*t*	Normal	Student-*t*	Normal	Student-*t*	Normal	Student-*t*
μ	0.0016*	0.0022*	0.0017*	0.0014*	0.0017*	0.0023*	0.0016*	0.0020*	0.0007	0.0009**
	(0.0004)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0008)	(0.0003)	(0.0004)	(0.0006)	(0.0004)
ψ_1	0.1154*	1.0049*	-	-	0.0711*	0.9969*	0.0698*	0.6013	0.8383*	-0.2782*
	(0.0148)	(0.1507)			(0.0163)	(0.0044)	(0.0154)	(0.3979)	(0.1199)	(0.0044)
ψ_2	-	-0.0122	-	-	0.0195	-	0.0051	0.2754	-	-0.9816*
		(0.1489)			(0.0161)		(0.0159)	(0.3262)		(0.0043)
θ_1	-	-0.9025*	-	-	-	-0.9333*	-	-0.5437	-0.7971*	0.2805*
		(0.1511)				(0.0165)		(0.3943)	(0.1322)	(0.0035)
θ_2	-	-0.0864	-	-	-	-0.0615*	-	-0.3073	-	0.9949*
		(0.1484)				(0.0161)		(0.3106)		(0.0038)
ω	0.00002*	0.00002*	0.00002*	0.00001*	0.00002*	0.00002*	0.00001*	0.000009*	0.00004*	0.00002*
	(0.000003)	(0.000004)	(0.000002)	(0.000003)	(0.000002)	(0.000004)	(0.000001)	(0.000002)	(0.000004)	(0.000004)
α_1	0.1427*	0.1554*	0.1712*	0.1242*	0.0978*	0.1068*	0.1248*	0.1199*	0.1234*	0.1181*
	(0.0086)	(0.0137)	(0.0123)	(0.0154)	(0.0064)	(0.0112)	(0.0076)	(0.0115)	(0.0117)	(0.0188)
β_1	0.8384*	0.8256*	0.8190*	0.8686*	0.8890*	0.8783*	0.8690*	0.8751*	0.8294*	0.8676*
	(0.0085)	(0.0133)	(0.0105)	(0.0142)	(0.0064)	(0.0116)	(0.0068)	(0.0104)	(0.0137)	(0.0180)
$\ln(L)$	10965.27	11060.15	6147.780	6261.278	8914.772	8992.672	9793.694	9896.512	4190.588	4344.711
AIC	-4.46174	-4.49965	-4.55601	-4.63944	-4.25748	-4.29272	-4.67751	-4.72522	-4.54599	-4.71273
SIC	-4.45513	-4.48775	-4.54726	-4.62850	-4.24839	-4.28061	-4.66842	-4.71158	-4.52801	-4.68574
$Q(20)$	42.604*	42.889*	17.562	16.981	30.905**	34.482*	40.161*	32.822*	18.666	28.102**
ARCH(4)	9.1412***	7.8968***	8.7876***	14.3249*	12.4048**	10.5479**	12.9413**	14.7333*	2.3287	1.7075
ARCH(5)	9.7290***	8.2878	8.8344	14.3938**	13.7537**	11.6298**	13.9407**	15.8337*	2.3489	1.7763

Notes: ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. RBD(4) represents the Residual Based Test of Tse (2001) statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

Break analysis results in Table 23 indicate seven general results: (I) these breaks show intensity generally at 1990 and 2000 years. Therefore indices seem to be effected by both endogenous and exogenous shocks in these years. The most effecting factor is emerging market crisis in the late 1990. The indices most severely affected by the crisis of Asia in 1997, Russia in 1998, and Brazil in 1999 are ISESRV (with 9 breaks), ISEIND (with 8 breaks), and ISEFIN (with 7 breaks). Hence, the real sector is significantly affected by foreign financial crises.

(II) The result that volatility shifts in ISEFIN and ISEIND exhibit continuity since the early 1990s indicates the existence of continuous fragility against external and internal shocks.

(III) Not surprisingly, 1994 and 2001 domestic financial crises lead breaks in all indices. The impact of 1994 crisis on technology and services indices can not be seen since the opening date of these indices realized afterwards. 2001 crisis in Turkey leads volatility shifts in indices, especially in ISESRV, ISEIND, and ISETECH (with 3 breaks).

(IV) Although the process of reconstruction in financial system and the precautions resulting in macroeconomic stability, the indices still exhibit volatility breaks. Approximately half of the volatility shifts in ISE100, ISEFIN, ISEIND, and ISESRV has occurred after 2000, which suggest that the so called indices seem very fragile against exogenous shocks.

(V) Intense capital movement in 2003 may cause volatility shifts in ISEFIN, ISEIND, and ISETECH. While portfolio investment movements lead volatility breaks in ISEFIN, shifts in ISEIND and ISETECH can be explained by the effects of exchange rate fluctuations caused by capital movement in industrial and technology sectors. The effect of exchange rate on real economy is more crucial especially in emerging markets.

(VI) Among others, financial index is the only one that has a break just after 2001 crisis (1 November 2002).

(VII) The recent fluctuation in foreign exchange market, occurred in June 2006, mostly affected industrial, ISE100, ISESRV and ISETECH indices. Expectedly, the real sector is sensitive to foreign exchange movements.

Table 23 Break dates for ISE indices with normal distribution

Break Number	Break Date				
	ISE100	ISEIND	ISEFIN	ISESRV	ISETECH
1	October 17, 1988	February 5, 1991	February 24, 1992	March 31, 1997	November 27, 2000
2	December 12, 1988	November 13, 1991	January 29, 1993	June 27, 1997	December 8, 2000
3	February 23, 1989	December 2, 1991	December 31, 1993	October 10, 1997	February 13, 2001
4	March 8, 1989	March 4, 1992	June 24, 1994	March 2, 1998	February 23, 2001
5	September 8, 1989	May 22, 1992	October 24, 1997	August 7, 1998	November 30, 2001
6	February 24, 1992	July 27, 1992	February 23, 1998	November 24, 1998	February 28, 2003
7	July 10, 1992	January 29, 1993	August 7, 1998	July 13, 1999	March 19, 2003
8	January 29, 1993	July 28, 1993	November 25, 1998	September 8, 1999	April 16, 2003
9	January 7, 1994	January 7, 1994	September 6, 1999	November 3, 1999	September 26, 2003
10	June 17, 1994	June 17, 1994	October 21, 1999	April 28, 2000	October 13, 2003
11	October 25, 1994	April 18, 1995	December 8, 1999	December 8, 2000	May 7, 2004
12	December 29, 1994	May 23, 1995	January 31, 2000	February 16, 2001	February 16, 2005
13	October 24, 1997	November 24, 1995	May 5, 2000	February 26, 2001	May 4, 2005
14	February 25, 1998	March 5, 1996	May 9, 2000	May 9, 2001	August 3, 2005
15	August 7, 1998	January 22, 1997	November 17, 2000	March 19, 2003	August 5, 2005
16	November 25, 1998	January 28, 1997	March 30, 2001	July 20, 2004	May 11, 2006
17	October 21, 1999	June 27, 1997	December 6, 2001	July 26, 2004	July 20, 2006
18	November 25, 1999	October 24, 1997	November 1, 2002	April 28, 2005	
19	April 17, 2000	February 27, 1998	March 25, 2003	October 11, 2005	
20	November 17, 2000	August 7, 1998	September 26, 2003	October 19, 2005	
21	March 12, 2001	November 25, 1998	December 1, 2003	May 11, 2006	
22	July 19, 2001	December 9, 1999	June 8, 2004	July 28, 2006	
23	February 28, 2003	March 1, 2000	July 6, 2007	June 26, 2007	
24	March 25, 2003	November 17, 2000	August 22, 2007		
25	September 26, 2003	December 7, 2000			
26	December 1, 2003	February 16, 2001			
27	June 14, 2004	February 23, 2001			
28	May 11, 2006	April 27, 2001			

29	July 20, 2006	February 28, 2003			
30	July 6, 2007	March 25, 2003			
31	August 22, 2007	May 14, 2003			
32		September 26, 2003			
33		December 1, 2003			
34		June 14, 2004			
35		March 6, 2006			
36		March 14, 2006			
37		May 11, 2006			
38		May 26, 2006			
39		July 20, 2006			
40		February 26, 2007			

Detailed break index analysis show that ISE100 exhibits continuous fragility through the permanent volatility shifts since 1998. However, the decrease in shifts after 2000 could be explained by implementations about macroeconomic stability and reconstructions process in the financial sector. It is expected that financial liberalization process in 1989 causes volatility breaks in the index. Later, breaks exist due to crisis in 1994, emerging market crisis, and crisis in 2001. Also, similar effects of capital movement and fluctuations in Exchange market may lead volatility breaks in 2003 and 2006.

Volatility breaks in ISESRV has become frequent after 2000, and has kept on occurring occasionally. Like crisis in 2001, the major impact of emerging market crisis on index can be seen clearly. However, the breaks occurring in the second part of 2006 may be explained by the effect of the movement activity on service sector. The fact that breaks in ISEFIN separate equally between in 1990 and in 2000 suggests the continuous fragility against external and internal shocks. Even decreased, so called fragility has been continuing now. Moreover, the accrual of four breaks in 2000 can be considered as the leading indicator of 2001 financial crisis. However, this consideration is not valid for emerging market crisis since there is not volatility breaks before emerging market crises in 1995 and 1996. On the other hand, there is a break in ISEFIN just after the 2001 crisis. In this respect, it is the only index that has a break in 2002 (November 1, 2002). Finally, it is anticipated that intense capital movements in 2003 causes three volatility breaks in ISEFIND.

Similar to other indices, ISEIND index exhibits intense volatility breaks in 1990s and 2000s. Breaks in early 1990s can be considered as the result of reflection of Gulf Crisis in industrial production. Emerging market crisis seems to affect ISEIND severely indicates the possible effect of fluctuations in exchange rate on industrial production. Similar effect leads volatility shifts in 2003 and 2006. Intensity of volatility breaks in the second part of 2006 can be explained by the activities in the exchange rate market. Breaks in ISETECH can be explained by the sectoral impacts.

As shown in Table 24, volatility persistence drastically reduces for all indices except for ISEIND index when break dates are introduced to GARCH(1,1) model, which indicates that volatility shifts are a likely source of long memory in volatility for all, but ISEIND index. Under the normal distribution assumption, ISESRV exhibits the greatest reduction in volatility persistence by %36.9, followed by ISE100 with a %35.7 decrease, finally ISEFIN with %13.3. On the other hand, under the normal distribution assumption, ISETECH index have the largest decline in volatility persistence by %40.7, followed by ISE100 with %37.9, then ISEFIN with %37.3, and finally ISESRV with %36.7. Moreover, Malik and Hassan (2004) highlight the importance of decrease in volatility persistence through breaks in terms of index-investing strategy and option pricing. Consistent with Aggarwal et al (1999), and Lamoureux and Lastrapes (1990), GARCH (1,1) model overestimates the volatility persistence when volatility breaks are not introduced to the model. Hence taking into account the volatility breaks in estimating volatility persistence is crucial for ISE. The number of days over which a shock to volatility decreases to half its original size are denoted the half-lives of volatility persistence and summarized in Table 25. ISESRV has the largest decrease in half life by approximately 94 days, which confirms the necessity of introduction of break dates to model for getting more accurate degree of persistence.

Table 25. Half-lives of shocks with and without the sudden changes.

index	Normal distribution		Student-t distribution	
	Without dummies	With dummies	Without dummies	With dummies
ISE100	37.327	2.504	37.134	2.397
ISESRV	71.382	2.471	96.923	2.490
ISEFIN	53.164	5.425	47.173	2.434
ISEIND	112.451	-	139.283	-
ISETECH	15.336	-	49.124	2.287

The formula of half-lives is given by $1-[\log 2/(\log(\alpha+\beta))]$

Table 24. GARCH(1,1) model with and without dummy variables

Index	GARCH(1,1) model							GARCH(1,1) model with dummy variables							
	α	β	$\alpha+\beta$	TR^2	$Q(20)$	LLH	AIC	α	β	$\alpha+\beta$	Persistence decline	TR^2	$Q(20)$	LLH	AIC
Panel A. Normal Distribution															
ISE100	0.1427* (0.0086)	0.8384* (0.0085)	**0.9811**	9.1412***	42.604*	10965.27	-4.4617	0.1038* (0.0241)	0.5269* (0.1081)	**0.6307**	**-0.3504**	115.9620* 141.3444*	62.032*	10077.48	-4.0873
Hizmet ISESRV	0.1712* (0.0123)	0.8190* (0.0105)	**0.9902**	8.7876***	17.562	6147.780	-4.5560	0.1146* (0.0293)	0.5096* (0.1196)	**0.6242**	**-0.366**	88.2680* 111.1842*	30.375***	5673.881	-4.1861
Mali ISEFIN	0.0978* (0.0064)	0.8890* (0.0064)	**0.9868**	12.4048**	30.905**	8914.772	-4.2575	0.1932* (0.0128)	0.6618* (0.0157)	**0.855**	**-0.1318**	2.3298 11.0570***	34.611**	8888.385	-4.2334
Simai ISEIND	0.1248* (0.0076)	0.8690* (0.0068)	**0.9938**	12.9413**	40.161*	9793.694	-4.6775	-0.0015* (0.00005)	0.9993* (0.000003)	**0.9978**	**0.004**	65.8683* 77.1610*	28.477***	9977.936	-4.7465
Teknoloji ISETECH	0.1234* (0.0117)	0.8294* (0.0137)	**0.9528**	2.3287	18.666	4190.588	-4.5460	0.0509* (0.0069)	0.9369* (0.0067)	**0.9878**	**0.035**	18.5475* 18.8635*	15.686	4346.100	-4.6990
Panel B. Student-*t* Distribution															
ISE100	0.1554* (0.0137)	0.8256* (0.0133)	**0.9810**	7.8968***	42.889*	11060.15	-4.4997	0.0998* (0.0245)	0.5090* (0.1134)	**0.6088**	**-0.3722**	176.0758* 257.7689*	45.101*	10306.12	-4.1796
Hizmet ISESRV	0.1242* (0.0154)	0.8686* (0.0142)	**0.9928**	14.3249*	16.981	6261.278	-4.6394	0.1116* (0.0350)	0.5165* (0.1530)	**0.6281**	**-0.3647**	82.8204* 118.3192*	28.717***	5717.181	-4.2174
Mali ISEFIN	0.1068* (0.0112)	0.8783* (0.0116)	**0.9851**	10.5479**	34.482*	8992.672	-4.2927	0.0954* (0.0299)	0.5213* (0.1471)	**0.6167**	**-0.3684**	52.5828* 64.7081*	37.854*	8295.933	-3.9484
Simai ISEIND	0.1199* (0.0115)	0.8751* (0.0104)	**0.9950**	14.7333*	32.822*	9896.512	-4.7252	-0.0026* (0.0002)	1.0004* (0.0003)	**0.9978**	**0.0028**	66.8296* 78.9557*	23.261	10015.90	-4.7632
Teknoloji ISETECH	0.1181* (0.0188)	0.8676* (0.0180)	**0.9857**	1.7075	28.102**	4344.711	-4.7127	0.1127* (0.0335)	0.4710* (0.1495)	**0.5837**	**-0.402**	49.5012* 63.8466*	36.015*	4006.233	-4.3263

Notes: TR^2s and Q(20) are ARCH LM and Ljung-Box Q statistics, respectively. $\alpha+\beta$ is the sum of the coefficients of the GARCH and ARCH terms and it is a measure of volatility persistence.

CONCLUSION

This thesis has examined the evidence of long memory in the daily returns and volatility of Turkish stock indices, namely ISE National - 100, ISE National – Services, ISE National – Financial, ISE National – Industrials, ISE National – technology. For this purpose, ARFIMA, FIGARCH, and ARFIMA-FIGARCH model was specified and estimated under the normal, student-t, and skewed Student-t distributions. Preliminary data analysis suggest that all indices have significant serial correlation and heteroscedasticitiy implying the necessity of AR(FI)MA and (FI)GARCH based modelling. Moreover, negative skewness and positive kurtosis existing in all indices, along with Jarque-Bera statistics suggest that indices have non-normal distribution. The estimation results of ARFIMA model suggest that ISE100, ISEIND, and ISEFIN indices have long memory while ISESRV and ISETECH indices have short memory. Since long memory denotes weak form market inefficiency, ISE100, ISEIND, and ISEFIN indices consists the effects of news and shocks occurring in the past; Thus speculative earnings can be gained via predicting price by using historic prices.

We investigate asymmetry and the leverage effect in ISE by using short memory models of EGARCH and GJR-GARCH, as well as long memory asymmetric model of FIEGARCH. Statistically insignificant asymmetry parameters suggest the absence of asymmetry or leverage effect in ISE. Thus, modeling volatility of ISE based on symmetric models is a more appropriate approach in terms of capturing volatility. GARCH model estimation results indicate that all indices have integrated garch effect; hence IGARCH model is used for modelling this effect. In contrast to short memory models, FIGARCH model could eliminate ARCH effect, which means FIGARCH is superior to the traditional short memory models. Most importantly, for all indices, long memory parameters in FIGARCH model are statistically significant indicating that the effect of shock on volatility remains at long lags. Hence we conclude that ISE is more sensitive than developed markets and emerging markets having short memory.

ARFIMA-FIGARCH model results indicate that ISE100, ISEIND, and ISEFIN indices have long memory in return and in volatility simultaneously. Moreover, estimation results of ARFIMA-FIGARCH and ARMA-FIGARCH models with different distributions reveal that Student-t distribution outperforms the Gauss distribution.

Beside the existence of long memory, we also investigate source of long memory. A literature proves that structural changes, switching regimes and occasional breaks may cause long memory in a time series. The major domestic or global economic and political events may affect volatility persistence since these events cause unstable stock prices, and thus volatility breaks. The iterated cumulated sum of squares (ICSS) algorithm proposed by Inclan and Tiao (1994) is used for detecting volatility shifts. Break analysis results indicate that volatility breaks are caused by global shocks, such as the crisis of Asia in 1997, Russia in 1998, and Brazil in 1999; as well as sectoral events. The results of B-GARCH model, which accounts for the effect of break dates detected by ICSS algorithm on variance, suggest that all indices except ISEIND overestimates volatility persistence when break dates are ignored. Thus, researchers studying the volatility should consider the volatility breaks. More importantly, volatility shifts may be the source of long memory in ISE100 and ISEFIN indices.

Fama (1970) states that investors, all of whom are rational, implement arbitrage quickly in case the existence of deviation in price changes in an efficient market. Thus it is impossible to gain abnormal returns. Three types of market efficiency are defined: weak form efficiency, semi-strong efficiency, and strong form efficiency. The weak form of the efficient market hypothesis suggests that past prices are not determinants of the futures prices. The semi strong form of the efficient market hypothesis claims that the prices impound the all publicly available information. Finally, the strong form of the efficient market hypothesis asserts that stock prices reflect all information, not only all public information.

In a weak form efficient market, past prices can not be determinants of futures prices due to fully reflection of information occurring in the past. Hence, price series follow random walk process. Making profits over market returns, or generating speculative gains are impossible.

Thus, efficient market hypothesis assume that series of price have no memory, which means that past and future prices are independent. Since the long memory of a series can be defined as dependence among distance prices, series with long memory pattern putrefies the weak form efficiency. Hence long memory of returns estimated by ARFIMA model contradicts the weak form market efficiency. Fama (1970) states that new information flow is quickly reflected in prices changes in an efficient market. Thus, the changes in price absorb the impact of news rapidly, which denotes that there is no dependence between distance price changes. Thus, dependence in price changes, so long memory in volatility, putrefies the weak form market efficiency indirectly through spoiling the pricing mechanism.

The estimation results of ARFIMA-FIGARCH model reveal that Istanbul Stock Exchange has double long memory property, which contradicts the weak form market efficiency. Thus future prices can be forecastable, which leads the possibility of speculative gains. In an inefficient market, information handling process regarding past prices along with firm specific and macroeconomic information, such as merger plan announcements, inflation, or unemployment, make it possible to gain abnormal returns. Moreover, techniques using past prices to forecast futures prices, such as technical analysis and charting, may be useful to forecast futures prices. techniques using financial information to search under priced stocks, such as fundamental analysis enable to gain abnormal returns in an inefficient markets, such as Istanbul stock exchange because not only prices are forecastable but also information flow have long run impact on volatility. Since Istanbul stock exchange is not an efficient market, the impact of firm-specific decisions on stock prices is ambiguous, thus stock prices can not be used as a measure of corporate performance.

These conclusions have some policy implications for risk managers and researchers studying on ISE; investors, and policy makers. Risk managers must consider the ARFIMA model since traditional Box-Jenkins method may not perform well if time series has long memory. Hence, researchers and risk managers analyzing or forecasting ISE100, ISEFIN, and ISEIND indices must use ARFIMA model instead of ARMA. In terms of analyzing volatility, asymmetric short and long memory volatility models; such as EGARCH, GJR-GARCH, FIEGARCH, are not appropriate for ISE due to insignificant asymmetry parameters. Thus, researchers and risk managers should use symmetric models. Most importantly, since long memory models of FIGARCH outperforms the traditional and popular GARCH and IGARCH model, variance series of ISE indices filtered by the FIGARCH model give more efficient results than short memory models based on risk analyzing methods requiring variance series, such as “value at risk”. Researcher using GARCH based models must consider the volatility shifts since taking into account volatility shifts reduce volatility persistence. Thus, analysis which ignores structural breaks may overstate the degree to which these breaks affect volatility may be misleading. Thus, ARFIMA-FIGARCH model is better for ISE100, ISEFIN, and ISEIND indices while ARMA-FIGARCH model gives superior results for ISESRV and ISETECH indices. Finally, when analyzing ISE, researchers should use Student-t distribution rather than Gauss distribution to get more realistic analysis results.

Since ARFIMA models reveal that long memory exists in ISE100, ISEFIN, and ISEIND indices, past information can be used for predict future prices to earn speculative gains. Therefore, especially small investors should be careful to speculative attacks in Istanbul Stock Exchange. Moreover, FIGARCH model results indicate that the effect of shocks on volatility in Istanbul Stock Exchange remains in a long period. Hence, investor should expect that shocks, which are global or local, affect ISE more severely than markets having short memory. Moreover break analysis suggest that global shocks and sectoral events severely affect indices, hence investors should take into account global and sectoral news.

Policy makers should take precaution to improve stock market efficiency in Turkey. In inefficient markets, the aim of capital movements is speculation rather than long term capital investment. Hence the real economic growth could not be sustainable since the function of financing the real sector through stock exchange markets does not work in inefficient markets. It is crucial that understanding how major economic and political events (either global or local) could correspond to regime shifts in the volatility of stock returns series and how shocks will affect volatility over time since FIGARCH model results indicate that effect of shocks on volatility lasts longer . As stated in Malik (2003), the persistence in volatility is an important parameter for accurately predicting how major events could affect future stock return volatility.

Limitation of this thesis may be related to the utilization of the data range. Data of ISE100 index before 1988 is not inappropriate to investigate in terms of orderliness of the data. Moreover data range of ISESRV and ISETECH are relatively short as compared with other indices

For further research, long memory property of ISE via high frequency data may be investigated. Furthermore, spillover effects of ISE should be examined via multivariate models.

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APPENDIX A. ARFIMA MODELS

White noise process is defined as

$$y_t - \mu = \varepsilon_t \tag{1}$$

where μ is the mean of time series y_t and ε_t is error term. $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma^2$ and $E(\varepsilon_t, \varepsilon_s) = 0$ for s≠t. meaning of the last assumption is that each observation is uncorrelated with all other values. Consequently, in a white noise process, autocorrelation function is zero for all lags except lag zero.

Granger (1980), Granger and Joyeux (1980), and Hosking (1981) developed fractional white noise process defined as

$$(1 - L)^{\xi}(y_t - \mu) = \varepsilon_t \tag{2}$$

Where L is the lag operator and $(1 - L)^{\xi}$ is fractional difference operator. As similar as white noise process, $E(\varepsilon_t) = 0$, $E(\varepsilon_t^2) = \sigma^2$ and $E(\varepsilon_t, \varepsilon_s) = 0$ for s≠t. Additionally, the fractional parameter, ξ, is likely to be noninteger. In case of ξ < (0,5), the process is weakly stationary; and it is invertible when ξ > (0,5). The infinite-order autoregressive representation of white noise process is (Ballie, 1996)

$$y_t = \sum_{k=0}^{\infty} \pi_k y_{t-k} + \varepsilon_t \tag{3}$$

Where k is the lag and π_k is the infinite autoregressive representation coefficient defined as

$$\pi_k = \Gamma(k - d) / \{\Gamma(-d)\Gamma(k + 1)\}$$

(4)

where $\Gamma(.)$ is gamma function. In the same way, infinite-order moving average representation, Wold decomposition, can be defined as

$$y_t = \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k} \tag{4}$$

Where ψ_k is the infinite autoregressive representation coefficient defined as

$$\psi_k = \Gamma(k+d)/\{\Gamma(d)\Gamma(k+1)\} \quad (5)$$

Where $\Gamma(.)$ is gamma function.

Granger and Ding (1996) proposed that a time series has long memory in case of having hyperbolic decaying autocorrelation function (ACF) and an infinite spectrum at zero frequency. This situation can be defined as

$$\rho(k) \approx c|k|^{2\xi-1} \quad , \quad \sum_{k=-\infty}^{\infty} |\rho(k)| = \infty \qquad \text{as } |k| \to \infty \quad (11)$$

The hyperbolic decay that is evidence of long memory in ACF contradicts an exponential rate of decay named short memory described as

$$|\rho(k)| \leq ba^k \quad , \; 0<b<\infty \text{ and } 0<a<1 \quad \sum_{k=-\infty}^{\infty} |\rho(k)| < \infty \quad (12)$$

Consequently, the investigating decaying pattern of ACF is a way of determining whether series produce long memory (Maheu 2002).

Although analyzing ACF is useful method for identifying whether time series has long memory property, parametric and semi-parametric methods can be used for estimating d parameter determining the memory specifications of time series. Exact Maximum Likelihood-EML (Sowell 1992), Appropriate Maximum Likelihood (Fox and Taqqu 1986) (Li and McLeod 1986) are some of the parametric methods; Geweke and Porter-Hudak (hereafter denoted GPH) (1983) is semi parametric method.

Autoregressive Fractional Integrated Moving Average (ARFIMA (p,d,q)) models are proposed and improved by Granger (1980), Granger and Joyeux (1980), and Hosking (1981) and defined as

$$\phi(L)(1-L)\xi(y_t - \mu) = \theta(L)\varepsilon_t \qquad \varepsilon_t \sim i.i.d.(0, \sigma_{\varepsilon_t}) \quad (6)$$

where L is the lag operator and $(1-L)^d$ is fractional difference operator. μ is the unconditional mean of y^t. $\phi(L)$ is autoregressive operator and $\theta(L)$ is moving average operator. $\phi(L)$ and $\theta(L)$ are the polynomials of order p and q, respectively and mathematical definition of polynomials are

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p = 1 - \sum_{j=1}^{p} \phi_j L^j \tag{7}$$

$$\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q = 1 + \sum_{j=1}^{q} \theta_j L^j \tag{8}$$

Fractional difference operator, $(1-L)^d$ defined as

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)} L^k \equiv \sum_{k=0}^{\infty} \pi_k(d) L^k \tag{9}$$

$$= 1 - dL + \frac{d(d-1)}{2!} L^2 - \frac{d(d-1)(d-2)}{3!} L^3 + \ldots \tag{10}$$

with denoting $\Gamma(.)$ the gamma function described as $\int_0^{\infty} x^{g-1} e^{-x} dx$ and $\pi_k(z) = \Gamma(k-z)/\Gamma(k+1)\Gamma(-z)$. Time series y^t is fractionally integrated white noise when polynomials of ARFIMA model equal one.

The stationary and invertibility conditions of y^t are that all roots of polynomials must lie outside the unit circle and $|\xi| < 0{,}5$ making effects of innovations to decay slowly to zero. However, if 0.5<ξ, y^t is not covariance stationary because of having infinite variance. If -0.5<ξ<0, ARFIMA process shows antipersistence meaning returns are very likely to increase in the next period when they decrease in a given period and vice versa. In addition, it has intermediate memory, in other words it exhibits long range negative dependence. When ξ=0, ARFIMA process transforms into stationary and invertible ARMA process and it has short memory and the effect of innovation declines geometrically. The process has long memory or long range dependence and persistency in case of 0< ξ<0.5. Autocorrelation function of time series having long memory, $\rho(k)$, decays hyperbolically toward zero in contrast geometric decay of ARMA process since $\rho(k)$ is proportional to $k^{2\xi-1}$ as $k \to \infty$. This relation is described as $\rho(k) \sim Ck^{2\xi-1}$.

K denotes displacement in time and c denotes the constant depending on the parameters of the model, a hyperbolic term but not k. If $0.5 \le \xi < 1$, the process is not covariance stationary, but mean reverting since the future values of the process are not influenced by the innovation in long run (Barkoulas et al, 1996). When ξ=1, the impact of innovations shows infinite persistence in all future periods since the process follows unit root (Kang et al,2006). There is no invertible representation of the process if -1< ξ<-0.5. Finally, when $|\xi| > 1$, the process is not mean-reverting (Limam 2003). The table below summarizes the memory specifications dependent on value of parameter d.

Table 26.Memory specifications of a series dependent on value of d parameter

Interval	Memory specification
$-0.5 < \xi < 0$	Short memory Volatility persistent
$0 < \xi < 0.5$	Long memory Stationary
$\xi = 0$	Short memory Stationary
$0.5 \le \xi < 1$	Not covariance stationary Mean reversion Finite impulse response weight
$1 \le \xi$	Not covariance stationary Not mean reversion

APPENDIX B. MODELS OF LONG AND SHORT MEMORY IN VOLATILITY

Although the returns are serially correlated, the absolute returns and their power transformations are highly correlated. This feature of the returns is named "Taylor Effect" by Granger and Ding (1995).

A long memory conditional variance process can be established from the identical bases. The mean equation of the return series denoted R_t defined as

$$R_t = f\left(x_t\right) + \varepsilon_t \tag{16}$$

where $\varepsilon_t \left| I^{t-1} \sim i.i.d.(0,\sigma_t^2)\right.$ meaning the disturbing terms identically and independently distributed with zero mean and finite time dependent variance based on the information set up to time *t-1* denoted I^{t-1}. $f\left(x_t\right)$ denotes the functional model of explanatory variable x_t. Generally, $f\left(x_t\right)$ equals to the conditional mean of R_t denoted μ_t (Wilkins 2004).

In order to model and forecast the conditional variance, Engle (1980) proposed the ARCH model of which the main idea is that the conditional variance is a linear function of past squared residuals. ARCH(q) model is defined as

$$\varepsilon_t = \sigma_t z_t \tag{17}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 \tag{18}$$

where *L* is the lag operator and $\alpha_0 > 0$ and $\alpha_i \geq 0$ (i = 1,2,…,q). $E\left[z_t \middle| I^{t-1}\right] = 0, \mathrm{var}\left[z_t \middle| I^{t-1}\right] = 1$. Thus, z_t is identically and independently distributed with zero mean and one variance. Although the ARCH model has the characteristic of uncorrelated residuals ε_t because z_t is i.i.d.(0,1), autocorrelation exists not only between squared returns, but also between the returns and their power transformations (Granger and Ding 1996) . Bollerslev (1986) included lagged variables of the variance to eliminate autocorrelation of absolute and squared error terms and generalized the GARCH (p, q) model defined as

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 = \alpha_0 + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{19}$$

where *L* is the lag operator and $\alpha_0 > 0$ and $\alpha_i \geq 0$ (i = 1,2,…,q) and $\beta_i \geq 0$ to ensure σ_t^2 is always positive . $\alpha(L)$ and $\beta(L)$ are the lag polynomials. All the roots of $\alpha(L)$ and $\{1-\alpha(L)-\beta(L)\}$ are restricted to lie outside the unit circle.

In the GARCH (p,q) model, q lagged variable of error term and p lagged variable of conditional variance influence the current conditional variance. Consequently, this model captures volatility clustering meaning that small (large) price changes are followed by small (large) price changes. Though the advantage of measuring volatility clustering, GARCH model has two major drawbacks. First, GARCH models can not capture asymmetric effect on the volatility meaning that positive return shocks are likely to cause less volatility than a negative return shocks. Second, GARCH models can not determine whether shocks to conditional variance persist or not. Many applications have developed the extensions of the GARCH model, such as IGARCH and EGARCH models, to overcome these drawbacks (Kang, Yoon 2006).

Nelson (1991) introduced the Exponential GARCH (EGARCH) model to accommodate asymmetric effect on the volatility. Bollerslev and Mikkelsen (1996) improved EGARCH model as follows

$$\ln(\sigma_t^2) = \alpha_0 + [1-\beta(L)]^{-1}[1+\alpha(L)]g(z_{t-1}) \tag{20}$$

$$g(z_t) = \gamma_1 z_t + \gamma_2 [|z_t| - E|z_t|] \tag{21}$$

with $z_t = \varepsilon_t \big/ \sqrt{\sigma_t^2}$, and the function $g(z_t)$ is independently and identically distributed with zero mean. Log specification allows makes conditional variance is positive for all possible choices of the parameters of the process. To capture the asymmetric effect on the volatility, the function $g(z_{t-1})$ is substituted for the lagged squared disturbance terms in the GARCH modeling. If z_t is negative, the slope of the $g(z)$ is $\gamma_1 - \gamma_2$; however, when z_t is positive the slope of the $g(z)$ is $\gamma_1 + \gamma_2$. Consequently, asymmetric response to the z_t depending on their sign, which is important property for modeling the leverage effect in stock market is taken into account by the model. For instance, for $\gamma_1 = 0$ and γ_2 is negative, the innovation is negative (positive) if the z_t is smaller (bigger) than its expected value. In case of $\gamma_1 = 0$ and γ_2 is positive, the innovation is negative (positive) when z_t is larger (smaller) than its expected value (Kang, Yoon 2006).

Bollerslev (1986) showed that equation (19) can be rewritten to give ARMA (m,p) process in ε_t^2, where *m=max(p,q)*

$$[1-\alpha(L)-\beta(L)]\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t \tag{21}$$

$$v_t = \varepsilon_t^2 - \sigma_t^2 \tag{22}$$

where v_t is error component in conditional variance, or innovations for the conditional variance. All the roots of the polynomial of $[1-\beta(L)]$ must lie outside the unit circle to ensure conditional variance to be non negative.

To capture infinite persistence, Engle and Bollerslev (1986) introduced the integrated GARCH (p,q), IGARCH (p,q) model by permitting the autoregressive polynomial of $[1-\alpha(L)-\beta(L)]$ to accommodate unit root. The IGARCH (p,q) is given by

$$\phi(L)(1-L)\varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t \tag{23}$$

Where $\phi(L) = [1-\alpha(L)-\beta(L)](1-L)^{-1}$ is of order *m-1*.

Since the sum of GARCH coefficients ($\sum_{i=1}^{q}\alpha_i and \sum_{j=1}^{p}\beta_j$) is generally close to unity in high frequency data, the IGARCH process is empirically important. However, IGARCH models assume volatility has infinite memory, that is, volatility shocks never dies out. Thus, difference between *I(0)* and *I(1)* process is too narrow for modeling long memory in conditional variances. It results that IGARCH models can not be used for long memory in the volatility process (Kang and Yoon 2006).

Ballie, Bollerslev, and Mikkelsen (1996) proposed Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasicity Model (FIGARCH) by substituting fractional differencing operator, $(1-L)^d$, for integer difference operator, $(1-L)$, of IGARCH(p,q) process in Equation (23). Thus, ARMA (m, p) representation of FIGARCH (p,d,q) model becomes

$$\phi(L)(1-L)^d \varepsilon_t^2 = \alpha_0 + [1-\beta(L)]v_t \tag{24}$$

with $\phi(L) = 1-\phi_1 L - \phi_2 L^2 - ... - \phi_q L^q = 1-\sum_{j=1}^{q}\phi_j L^j$

$\beta(L) = 1-\beta_1 L - \beta_2 L^2 - ... - \beta_p L^p = 1-\sum_{j=1}^{p}\beta_j L^j$.

All roots of $\phi(L)$ and $[1-\beta(L)]$ must lie outside the unit circle. Fractional differencing operator is defined as

$$(1-L)^d = \frac{(n-d-1)!}{n!(-d-1)!}L^n \tag{25}$$

for $n = 1,2,...,\infty$. Alternatively, the FIGARCH (p,d,q) model can be redefined as,

$$[1-\beta(L)]\sigma_t^2 = \alpha_0 + [1-\beta(L)-\phi(L)(1-L)^d]\varepsilon_t^2 \tag{26}$$

From the representation above, infinite ARCH representation of FIGARCH process or conditional variance of ε_t^2 can be obtained by using the representation above. Infinite ARCH representation of FIGARCH process is

$$\sigma_t = \frac{\alpha_0}{1-\beta(1)} + \left[1-\frac{\phi(L)}{1-\beta(1)}(1-L)^d\right]\varepsilon_t^2 \equiv \frac{\alpha_0}{1-\beta(1)} + \lambda(L)\varepsilon_t^2 \tag{27}$$

where $\lambda(L) = \lambda_1(L) + \lambda_2(L)^2 + ...$ .All the coefficient in the infinite ARCH representation must be positive for nonnegative conditional variance. It is possible to prove nonnegativity conditions in a case by case basis since it is difficult to establish general conditions for nonnegativity of lag coefficients in $\lambda(L)$. for $0 < d < 1$, λ_1=0 the second moment of the unconditional distribution of ε_t is finite; consequently , FIGARCH process is not covariance stationary. However, for $0 < d \leq 1$, the FIGARCH process is strictly stationary and ergodic. Thus, even if FIEGARCH process is not weakly stationary, it is ergodic and weakly stationary (Kılıç 2004).

In FIGARCH model, fractional differencing parameter, d, measures the persistence of shocks in conditional variance. Consequently, the FIGARCH process takes into account intermediate range of persistence for $0 < d < 1$. When d equals to zero, FIGARCH (p,0,q) is the same model as GARCH(p,q) model. Thus, there is a resemblance with trend stationary or I(0) process. For d =1, FIGARCH(p,1,q) is identical to IGARCH(p, q) and similar to an I(1) process in the mean.

Bollerslev and Mikkelsen (1996) extended EGARCH model in Equation (20) by substituting autoregressive polynomial $[1-\beta(L)]$ for $\phi(L)(1-L)^d$ to factorize polynomial and account for asymmetries. The FIEGARCH (p,d,q) model is

$$\ln(\sigma_t^2) = \alpha_0 + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g(z_{t-1}) \tag{28}$$

$$g(z_t) = \gamma_1 z_t + \gamma_2 [|z_t| - E|z_t|] \tag{29}$$

Where all roots of $\phi(L)$ and $\alpha(L)$ lie outside the unit circle. Although long memory characteristics scatters for d<1, conditional mean, $\ln(\sigma_t^2)$, is invertible and covariance stationary for the interval of $-0.5 < d < 0.5$. That FIEGARCH(p,d,q) model does not set the nonnegativity constraints on the estimated parameters in contrast to FIGARCH (p,d,q) model makes the FIGARCH (p,d,q) model inferior and the order of the model be well defined (Kang and Yoon 2004). When d=1, FIEGARCH (p,d,q) process becomes integrated EGARCH, IEGARCH. However, in case of d=0, process transforms into EGARCH proposed by Nelson (1991).

Quasi Maximum Likelihood, hereafter QML, approach based on maximizing the normal likelihood function is used for estimating the parameters and appropriate mean equation specification. Normal likelihood function is denoted as

$$Q\left(\theta;\{\varepsilon_t\}_{t=1\ldots T}\right)=\frac{T}{2\log(2\pi)}-\frac{1}{2}\sum_{t=1}^{T}\left[\log\sigma_t^2+\varepsilon_t^2/\sigma_t^2\right] \qquad (30)$$

where T is the sample size and θ denotes the set of parameters. When conditional variance and conditional mean are specified correctly, QML estimators gotten under the assumption of normality are consistent (Caporale 2003). Standard error of $\hat{\theta}_t$ are obtained from the asymptotic distribution below

$$\hat{\theta}_t \sim N(\theta_0, T^{-1}A(\hat{\theta}_t)^{-1}B(\hat{\theta}_t)A(\hat{\theta}_t)^{-1}) \qquad (31)$$

where $B(.)$ is the outer product of the gradient and $A(.)$ is the Hessian matrix.

APPENDIX C. ICSS ALGORITHM

Inclan and Tiao (1994) developed the iterated cumulative sums of squares algorithm (the icss algorithm) based on D_K statistics to specify the existence of multiple breaks in variance in time series data. The icss algorithm assumes that time series has a stationary variance over an initial period till an unforeseen change in variance resulting from an exogenous shock. Then, the variance has a stationarity again at its new level until the existence of the subsequent shock. A time series observations with an unknown number of changes are obtained by repeating this process (Cochran et al 2004).

$$\sigma_2^t \begin{cases} \tau_0^2 & 1<t<K_1 \\ \tau_1^2 & K_1<t<K_2 \\ \ldots & \ldots \\ \tau_M^2 & K_{N_T}<t<T \end{cases} \tag{44}$$

where σ_t^2 is the unconditional variance of ε_t which is uncorrelated random variable and normally distributed with zero mean. $1 < K_1 < K_2 < \ldots < K_{N_T} < T$ denotes the set of change points. τ_j^2 refers to the variance of each period, $j = 0,1,\ldots, N_T$, where N_T denotes the total number of variance chances in *T* observations. In order to detect the number of variance and time point of occurrence of each shift, before a cumulative sum of squares is defined as $C_k = \sum_{t=1}^{k} \varepsilon_t^2, k = 1,\ldots T$, then D_K statistic is calculated as follows (Aggarwal et al 1999):

$$D_k = \frac{C_k}{C_t} - \frac{k}{T} \qquad k = 1,\ldots,T \quad \text{with} \quad D_0 = D_t = 0. \tag{45}$$

D_k statistics fluctuates around zero in case of no changes over the period. Nevertheless, when one or more chances in the variance exist, D_k statistics departures from zero either up or down from zero. The null hypothesis of homogenous variance over the entire period meaning no sudden variance change is tested by $\max_k |D_k|$. Suppose k^* be the point of *k* at which $\max_k |D_k|$ is obtained. It is concluded that k^* is a change point of variance, when $\max_k \sqrt{T/2}|D_k|$ exceeds the predetermined boundary estimated by Inclan and Tiao (1994). the factor of $\sqrt{T/2}$ is used for Standardizing the distribution.

The ICSS algorithm process is as follows (see Inclan and Tiao (1994) for details):

Let $a[t_1 : t_2]$ be the series $a_{t_1}, a_{t_1+1}, a_{t_1+2}, ..., a_{t_2}, t_1 < t_2$. The notation $D_k(a[t_1 : t_2])$ denotes the range over which the cumulative sums are obtained.

Step 0: $t_1 = 1$

Step 1: compute $D_k(a[t_1 : T])$. $k^*(a[t_1 : T])$ denotes the point for which $\max_k |D_k(a[t_1 : T])|$ is attained. Let $M(t_1 : T) = \max_{t_1 \le k \le T} \sqrt{(T - t_1 + 1)/2}|D_k(a[t_1 : T])|$. If $M(t_1 : T) > D^*$, D^* denotes critical value , there is a breakpoint at $k^*(a[t_1 : T])$ and algorithms continues to detect breakpoints. Otherwise, the algorithm stops because there is no breakpoint in time series data.

Step 2a: let $t_2 = k^*$ and calculate $D_k(a[t_1 : t_2])$. When $M(t_1 : T)$ exceeds the critical value, a new change point occurs and. Then, $k^*(a[t_1 : t_2])$ denotes the point for which $\max_k |D_k(a[t_1 : T])|$ is attained. Step 2 should be repeated till $M(t_1 : t_2) < D^*$. Consequently, the first breakpoint is $k_{first} = t_2$.

Step 2b: let $t_1 = k^*(a[t_1 : T]) + 1$ and calculate $D_k(a[t_1 : T])$. Till $M(t_1 : T) > D^*$, repeat step 2b. The last breakpoint denotes $k_{last} = t_1 - 1$.

Step 2c: there exists only one breakpoint, if $k_{first} = k_{last}$. Thus, algorithm stops. However, if $k_{first} < k_{last}$, let $t_1 = k_{first} + 1$ and $T = k_{last}$ then iterate step1 and step2. N_T refers to the overall number of breakpoints found.

Step 3: let *cp* denote the vector of the possible breakpoints, and they are sorted in increasing order. Let $cp_0 = 0$ and $cp_{N_T+1} = T$. Then calculate $D_k\left(a\left[cp_{j-1}+1 : cp_{j+1}\right]\right)$, $j = 1,2,...N_T$ to check breakpoints. If $M\left(cp_{j-1}+1 : cp_{j+1}\right)$ exceeds the critical value of D^*, the existence of breakpoint is confirmed and have to be modified in accordance with "maximum" rule. Otherwise, vector of breakpoint is eliminated. Step 3 is iterated till the number of breakpoints does not change and new found points are close to the points found previously (Bacmann and Dubois 2002).

While Lastrapes (1989) reveals that exogenously determined regime shifts decrease the volatility persistence in estimated ARCH model of exchange rates. Hamilton and Susmel (1994) proposed markow regime switching (SWARCH) model to detect endogenously determined regime switching. However, ICSS procedure is used for detecting endogenously shifts as a result of economic and political events. The effect of volatility breaks on the decrease of volatility persistence is estimated by the Break-GARCH (hereafter BGARCH) model with dummy variables corresponding to the break dates detected by ICSS procedure. BGARCH(1,1) can be expressed as follows:

$$R_t = \mu + \varepsilon_t \ , \qquad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \sigma_t)$$
$$\sigma_t^2 = \gamma + \xi_1 D_1 + \xi_2 D_2 + ... + \xi_N D_N + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where Ω_{t-1} is the information set and $D_1, D_2, ..., D_N$ denotes the dummy variables. The change in volatility persistence, that is the difference in $\alpha_1 + \beta_1$ of BGARCH(1,1) and GARCH(1,1)models, measures the effect of break dates on volatility.

APPENDIX D. DIAGNOSTIC TESTS

1. BDS test

BDS test proposed by Brock et al (1987) investigate the deviation from asymptotic $N(0,1)$ distribution. The null hypothesis that the time series have an asymptotic $N(0,1)$ distribution is tested by The BDS test statistics calculated as:

$$W_{m,T}(\varepsilon) = T^{0.5}\left[C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m\right] / \sigma_{m,T}(\varepsilon) \qquad (1)$$

Where $C_{m,T}(\varepsilon)$ denotes the correlation integral with embedding dimension of *m* and overlapping vectors of T_m , and calculates the probability that distance between two observations of the data is less than ε. The expected return of $\left[C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m\right]$ equals zero in case of white noise. $C_{m,T}(\varepsilon)$ is defined as :

$$C_{m,T}(\varepsilon) = \sum_{t<s} I_\varepsilon(x_t^m, x_s^m)\left[2/T_m(T_m - 1)\right] \qquad (2)$$

Where $T_m = T - (m-1)$ denotes the number of overlapping vectors. (see Blasco and Santamaria (1996) for details).

2. ARCH LM test

Engle proposed the Lagrange Multiplier (hereafter LM) test to detect presence of ARCH effects of the time series. The test statistics, nR^2 , is asymptotically chi squared distributed with degrees of freedom *q* and derived from the equation system below:

$$u_t^2 = \gamma_0 + \sum_s^q \gamma_s u_{t-s}^2 + e_t \qquad (1)$$

where *u* is the residual. The null hypothesis of time series has no ARCH effect implies no need to modeling volatility via (G)ARCH models.

3. Pearson Test

The comparison between the empirical distribution of the standardized residuals and theoretical distribution is held by Pearson goodness-of-fit test statistics with the number of *g* cells obtained from classifying the residuals in terms of their magnitude is as follows:

$$\sum_{i=1}^{g}\frac{\left(n_i - En_i\right)^2}{En_i} \sim \chi^2(g-1) \qquad (2)$$

Where n_i is the number of observations in group *i and* En_i is the expected number of observations. Since the choice of g is obscure, g is set to 60 (see Palm and Vlaar(1997), Beine and Laurent (2003) for details).

4. Residual Based Test

Residual Based (hereafter RBD) test proposed by Tse (2001) evaluates the sufficiency of the conditional variance structure. The null hypothesis that conditional variance structure is adequate is tested via the test statistics, *T(m),* iobtained from regression of $\hat{v}^2 - 1$ on a vector of lagged squared standardized residuals $\hat{u}_t = (\hat{v}_t^{\,2}, \hat{v}_{t-1}^2, \hat{v}_{t-m}^2)$, which can be expressed as:

$$\hat{v}_t^2 - 1 = \hat{u}_t'\theta + e_t \qquad (1)$$

$$T(m) = n\hat{\theta}'\hat{L}\hat{G}^{-1}\hat{L}\hat{\theta} \qquad (2)$$

Where $\hat{G} = \hat{c}\hat{L} - \hat{S}\hat{R}\hat{S}'$, $\hat{L} = \sum \frac{\hat{u}_t\hat{u}_t'}{n}$, $\hat{S} = \sum \hat{u}_t \frac{(\lambda\hat{v}_t^{\,2} / \lambda\varphi)}{n}$, $\hat{c} = \sum \frac{(\hat{v}_t^{\,2} - 1)^2}{n}$, and n is the number of observations (see Tsui (2004) for details).

5. Unit root test

Augmented Dickey- fuller (1979) (hereafter ADF) tests the null hypothesis that δ equals to zero, indicating series have unit-root. δ is obtained from the following equation:

$$\Delta y_t = \alpha + \beta t + \delta y_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

Optimum lag order, *p*, is included to eliminate the serial correlation and selected based on the model selection criteria, such as Akaike and Scwarz information criteria. Phillips-Perron (1988) (hereafter PP) tests the null hypothesis that δ equals to one, indicating series have unit-root. δ is obtained from the following equation:

$$y_t = \mu + \delta y_{t-1} + \beta (t - N/2) + \varepsilon_t \tag{2}$$

where N is the number of observations. Kwiatkowski et al (1992) propose a test (hereafter KPSS) more powerful than ADF or PP because KPSS tests the null of stationarity, which is the inverse of ADF and PP's null of nonstationarity. The null of ADF and PP is rejected when there is strong evidence against it. However, this approach may have low power against stationary near unit root process. According to the KPSS test, a time series consist deterministic trend, white noise, and stationary error term in the following regression:

$$y_t = \delta t + r_t + \varepsilon_t \tag{3}$$

where $r_t = r_{t-1} + u_t$, and $u_t \sim N(0, \sigma_u^2)$. KPSS is based on LM statistics associated with the error term obtained from regressing y_t against a constant and a trend. LM statistics is defined as:

$$LM = T^{-2} \sum_{t=1}^{T} S_t^2 / S_{\varepsilon_t}^3 \tag{4}$$

where S_t^2 denotes the partial sum of the residuals and $S_{\varepsilon_t}^3$ is the estimator of the variance of error term.

APPENDIX E. MODEL DENSITIES

Maximization of the Gaussian likelihood function logarithm to estimate the parameters of volatility models can be held via non-linear optimization procedures. Although linear models for the conditional mean and for the conditional variance assume that the distribution of the time series is Gaussian of which the log likelihood distribution (L_G) is defined as:

$$L_G = -0.5\sum_{t=1}^{T}\left[\ln(2\pi) + \ln(\sigma_t^2) + z_t^2\right] \tag{1}$$

where $z_t \sim N(0,1)$, *T* is the number of observations. However, vast literature reveals that Student-t distribution better captures the observed kurtosis. The log-likelihood function of the z_t with mean 0, variance 1, and degree of freedom *v* is as follows:

$$L_S = \ln\left[\Gamma\left(\frac{v+1}{2}\right)\right] - \ln\left[\frac{v}{2}\right] - 0.5\ln\left[\pi(v-2)\right] - 0.5\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+v)\ln(1+\frac{z_t^2}{v-2})\right] \tag{2}$$

Fernandez and Steel (1998) proposed Skewed student-t distribution to capture skewness in addition to kurtosis. The log-likelihood function of the skewed student-t is defined as:

$$\begin{aligned} L_{SkwT} &= \ln\Gamma\left(\frac{v+1}{2}\right) - \ln\Gamma\left[\frac{v}{2}\right] - 0.5\ln\left[\pi(v-2)\right] + \ln\left(\frac{2}{\gamma+\frac{1}{\gamma}}\right) + \ln(s) \\ &\quad - 0.5\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+v)\ln(1+\frac{sz_t+m}{v-2})\gamma^{I_t}\right] \end{aligned} \tag{3}$$

where $I_t = \begin{cases} -1 & if z_t < -m/s \\ +1 & if z_t \geq -m/s \end{cases}$

where γ measures the asymmetry. Skewed student-t distribution nests student-t distribution; thus, skewed student-t becomes student-t if $\gamma = 1$. The density is left skewed when $\ln(\gamma)$ is negative, vice versa. *S* and *m* are the standard deviation and mean of the skewed student-t distribution, respectively.

APPENDIX F. BREAK DATES FOR INDICES WITH STUDENT-T DISTRIBUTION

Break Number	Break Date				
	ISE100	**ISEIND**	**ISEFIN**	**ISESRV**	**ISETECH**
1	October 17, 1988	February 6, 1991	February 24, 1992	March 31, 1997	September 15, 2000
2	December 12, 1988	November 13, 1991	January 29, 1993	June 27, 1997	July 19, 2001
3	February 23, 1989	December 2, 1991	December 31, 1993	October 10, 1997	September 11, 2001
4	March 8, 1989	March 4, 1992	March 2, 1994	March 2, 1998	December 6, 2001
5	September 8, 1988	May 22, 1992	May 10, 1994	August 7, 1998	February 28, 2003
6	February 24, 1992	July 27, 1992	October 24, 1997	November 24, 1998	March 19, 2003
7	July 10, 1992	January 29, 1993	February 23, 1998	July 13, 1999	April 16, 2003
8	January 29, 1993	July 28, 1993	August 7, 1998	September 8, 1999	September 26, 2003
9	January 7, 1994	January 7, 1994	November 25, 1998	November 3, 1999	October 13, 2003
10	June 17, 1994	June 17, 1994	September 6, 1999	April 28, 2000	May 7, 2004
11	October 25, 1994	April 18, 1995	October 21, 1999	December 8, 2000	April 18, 2005
12	December 29, 1994	May 23, 1995	December 8, 1999	February 16, 2001	August 3, 2005
13	October 24, 1997	November 24, 1995	January 31, 2000	February 26, 2001	August 5, 2005
14	February 25, 1998	March 5, 1996	May 5, 2000	May 9, 2001	May 11, 2006
15	August 7, 1998	January 22, 1997	May 9, 2000	March 19, 2003	July 20, 2006
16	November 25, 1998	January 28, 1997	November 17, 2000	July 20, 2004	January 5, 2007
17	October 21, 1999	June 27, 1997	March 12, 2001	July 26, 2004	
18	November 25, 1999	October 24, 1997	July 19, 2001	April 28, 2005	
19	April 17, 2000	February 27, 1998	November 1, 2002	October 11, 2005	
20	November 17, 2000	August 7, 1998	March 25, 2003	October 19, 2005	
21	March 12, 2001	November 25, 1998	September 26, 2003	May 11, 2006	
22	July 19, 2001	December 9, 1999	December 1, 2003	July 28, 2006	
23	February 28, 2003	March 1, 2000	June 8, 2004	June 26, 2007	
24	March 25, 2003	November 17, 2000	July 6, 2007		
25	September 26, 2003	December 7, 2000			
26	December 1, 2003	February 16, 2001			
27	June 14, 2004	February 23, 2001			
28	May 11, 2006	April 27, 2001			
29	July 20, 2006	February 28, 2003			
30	July 6, 2007	March 25, 2003			

31	August 22, 2007	May 14, 2003			
32		September 26, 2003			
33		December 1, 2003			
34		June 14, 2004			
35		March 6, 2006			
36		March 14, 2006			
37		May 11, 2006			
38		May 26, 2006			
39		July 20, 2006			
40		February 26, 2007			