A MICROSTRUCTURAL APPROACH TO INTRADAY ANALYSIS OF TURKISH DERIVATIVES MARKET

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A MICROSTRUCTURAL APPROACH TO INTRADAY ANALYSIS OF TURKISH DERIVATIVES MARKET

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy.

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ABSTRACT

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This study provides a comprehensive analysis of the microstructure evolution of the Turkish derivatives market by examining the time-varying characteristics of asset returns. The research is aimed to improve the estimation of high-frequency intraday volatility as well as to highlight the impact of trading volume on intraday volatility specifications.

To examine the stability of the results, the dataset is divided into pre- and post-extension periods consistent with its extended trading hours after September 7, 2007. The findings indicate that volatility asymmetry is not present in Turkish derivatives market. Furthermore, the estimation results show that volatility patterns under GED assumption are more appropriate for modeling the intraday returns as opposed to conventional GARCH volatility modelings.

In order to accommodate the nature of information, the models are extended by allowing the trading volume to enter into volatility specification. The findings suggest that when there is no arrival of new information to all market traders at the same time, trading decreases and prices deviate substantially, implying a negative relation between information and volatility of returns which is also

a feature of inefficiency in the market. Moreover, the volatility persistence remains even after the inclusion of trading volume within each period.

Consequently, the results are consistent with the theoretical market microstructure literature and carry important implications for portfolio managers and market participants in obtaining accurate information about Turkish derivatives market dynamics for hedging and diversifying their portfolios.

Keywords: Market efficiency hypothesis, high-frequency volatility modeling, trading volume, ISE-30 index futures

ÖZET

TÜRK TÜREV PİYASASI'NIN GÜN İÇİ ANALİZİNDE
MİKRO YAPISAL YAKLAŞIM

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Bu çalışma, zaman içerisinde değişen varlık getirilerini inceleyerek Türk türev piyasasının mikro yapısının detaylı bir şekilde analiz edilmesini sağlar. Bu doğrultuda, varlık fiyatlarının gün içi volatilite yapısında işlem hacminin etkisini de göz önüne alarak modellemeyi amaçlamaktadır.

Vadeli İşlem ve Opsiyon Borsası'nda seans saatleri 7 Eylül 2007 tarihinden itibaren uzatılmıştır. Sonuçların tutarlılığını incelemek için, veri seti, seans saatlerinin uzatılmasını dikkate alarak seans süresi uzama dönemi öncesi ve sonrası olarak ikiye ayrılmıştır. Bulgular, volatilite asimetrisinin Türk türev piyasasında mevcut olmadığını gösterir. Bunun yanında, geleneksel GARCH volatilite modellemelerine göre, GED varsayımı altında incelenen volatilite yapılarının gün içi getiri modellemesinde en uygun performansı gösterdiği tespit edilmiştir.

Nispeten yeni olan Türk türev piyasasında güncel bilginin tüm yatırımcılara aynı zamanda ulaşmaması, işlem hacminin düşmesine, fiyatlarda ise önemli değişimlere neden olmuştur. Bu sonuç, işlem hacmi ve volatilite arasında negatif yönlü bir ilişkiyi göstermektedir ki bu da etkin olmayan bir piyasanın özelliğidir. Öte yandan, incelenen tüm dönemlerde işlem hacminin eklenmesiyle volatilite sürekliliğinde bir değişme gözlemlenmemiştir.

Sonuç olarak, elde edilen bulgular, teorik piyasa mikro yapısına ait literatür sonuçları ile uyumlu olup portföy yöneticilerinin ve yatırımcıların riskten kaçınmak ve portföylerini çeşitlendirmek amacıyla Türk türev piyasası ile ilgili doğru bilgiye ulaşması açısından önem taşımaktadır.

Anahtar Kelimeler: Piyasa etkinliği hipotezi, gün içi volatilite modellemesi, işlem hacmi, İMKB-30 endeksi vadeli işlem sözleşmesi

To

My Parents

And

My Husband

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
ASE	Athens Stock Exchange
ASX	Australian Stock Exchange
BIS	Bank of International Settlements
CBOE	Chicago Board Options Exchange
CME	Chicago Mercantile Exchange
EGARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
FIA	Futures Industry Association
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GED	Generalized Error Distributions
HKFE	Hong Kong Futures Exchange
HSI	Hang Seng Index
IGARCH	Integrated-GARCH
ISE	Istanbul Stock Exchange
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
KSE	Korea Stock Exchange
LIFFE	London International Financial Futures and Options Exchange
LL	Log-Likelihood Function
LM	Lagrange Multiplier
LSE	London Stock Exchange
MDH	Mixture of Distributions Hypothesis
NYSE	New York Stock Exchange

QQ	Quantile-Quantile
SEHK	Stock Exchange of Hong Kong
SIAH	Sequential Information Arrival Hypothesis
SSE	Singapore Stock Exchange
TAIFEX	Taiwan Futures Exchange
TEOS	TurkDEX Exchange Operations System
TGARCH	Threshold GARCH
TSE	Tokyo Stock Exchange
TurkDEX	Turkish Derivatives Exchange
WFE	World Federation of Exchanges

CHAPTER 1

INTRODUCTION

Volatility is a fundamental component to the theory and practice of many asset pricing, asset allocation, and risk management applications. The measurement of volatility has attracted considerable attention in recent years, largely motivated by its importance for researchers in financial economics and practitioners in financial markets. Its central status is highlighted by the explosive growth of derivative markets in the mid-nineteenth century. The derivatives and risk management industries aim to find optimal dynamic hedging strategies[1]. It is common knowledge that volatility varies over time in a stochastic style on a daily basis and that financial market volatility displays certain characteristics[2] that are specific to financial time-series (Bollerslev, 1986 and 1990). Therefore, a large number of time-varying volatility models that take into account these characteristics have been developed by researchers and practitioners. The essential feature of asset prices is their obviously increased volatility during periods with greater amounts of news or information. Following the studies of Merton (1980) and Nelson (1992), there is a growing interest among financial economists on the high level of precision with which

[1] Hedging refers to a strategy designed to minimize the risk of changes in the value of a portfolio composed of either financial assets or physical commodities (or both). If this value is highly correlated with the price of a futures contract, the risk can be significantly decreased by adding an opposite position in futures, so that changes in the portfolio value are offset by changes in the futures price.

[2] These characteristics are called *stylized facts* such as volatility clustering, time-varying conditional heteroskedasticity, and leptokurtosis.

volatility can be estimated under the diffusion assumption which is often invoked in theoretical studies. The basic insight is that returns obtained over arbitrarily short intervals are used to estimate precise volatility. As the best frequency, daily data is acquired by holding the first or the last observation of the trading day for the variable of interest is utilized in most of the empirical researches in finance, thus disregarding all intraday events. Due to the automatization advancement in financial markets and the enhanced developments of computer and information technology in the trading and reporting system, many financial markets have set up intraday databases, named *ultra-high frequency data* by Engle (2000), that record every single transaction together with its characteristics. This large data set and increased computing power have encouraged researchers to disaggregate their data into the micro level to better understand the macro system (Dacorogna *et al.*, 2001). Interestingly, this progress has not been limited to academic area, but has also affected the current trading environment, allowing a deeper understanding of market activity. Meanwhile, research based on high-frequency, intraday financial asset prices have documented a remarkable diversity of the intraday return volatility process across a variety of asset categories and market structures. As a result, the availability of high-frequency datasets[3] has rekindled the interest of researchers as a means to study the time-varying characteristics of asset return in order to improve estimation of precise volatility - an entity of great importance in today's economic decision making.

The recent availability of high-frequency data sets have the potential to uncover many important insights on the behavior of intraday financial market data and present the most relevant innovations in the field of the quantitative analysis of the financial markets in the dawn of the 21*st* century. Although microfinance has

[3] High-frequency data in finance is data that is recorded at frequencies higher than daily.

spawned a new area for research, the challenging and interesting problem for practitioners and researchers is to decide how to analyze high-frequency data in general and how to capture the special characteristics of financial transactions in particular. The availability of intraday transaction data fills this gap by motivating the research on intraday futures market characteristics of the Turkish Derivatives Exchange (TurkDEX), which is an interesting evolving financial market to investigate. Therefore, this research will enhance the understanding of Turkish derivatives market thoroughly and systematically by examining its volatility behavior and comparing the empirical results gathered for Turkey against the general results in developed countries.

The analysis of high-frequency financial data presenting unique characteristics is tied to the area of financial economics known as market microstructure. The market microstructure research is concerned with developing a detailed understanding of the trading process and the effects of that process on price formation. While much of the theoretical works in market microstructure have been developed over the last two decades, most of the interest in the econometric and empirical work has extended over the last decade. Many theoretical models of investor and market behavior have been proposed to explain the features of many financial time series. These studies attribute the observed intraday pattern to specialists' attempt to exploit their market power or to deal with the inventory and information asymmetry problems[4]. The high-frequency data research not only improves the theoretical understanding of the

[4] Microstructure models fall into the three general categories: inventory, market power, and asymmetric information models. In the inventory models (see Stoll, 1978; Amihud and Mendelson, 1980, 1982; Ho and Stoll, 1981), the spread is motivated as compensation for market makers for bearing the risk of holding undesired inventory. Market-power models (see Stoll and Whaley, 1990; Brock and Kleidon, 1992) link intraday variations in spreads to the monopoly power of specialists. Information models (see Copeland and Galai, 1983; Glosten and Milgrom, 1985; Easley and O'Hara, 1987; Admati and Pfleiderer, 1988; Madhavan, 1992; Foster and Viswanathan, 1994) focus on the adverse selection problem faced by market makers.

econometric theory, but also contributes to the practical application of financial models.

The Efficient Market Hypothesis[5] (EMH) predicts that stock prices are entirely determined by economic fundamentals. Within an intraday trading period, however, wild price oscillations ranging from seconds to minutes occur on the stock market. Prices could open and close at the same particular price level, but reveal turbulent fluctuations throughout a single trading session. If changes in corporate fundamentals cause price movements and if EMH holds, the persistent volatility must imply that news arrives continuously to the market. It is widely believed that trading in asset markets is induced by the arrival of new information in the market and the subsequent revisions of expectations by investors. Price and trading volume are regularly disseminated into the public to report the status of financial markets and these statistics are closely monitored by investors. This implies that market participants consider that disclosure of price and trading volume will increase their understanding of the market dynamics. Thus, the trading volume can reflect new information about changes in participants' expectations.

The theory on the return and trading volume relationship is also based on whether the information arrival process in financial markets is sequential or simultaneous. The Mixture of Distributions Hypothesis (MDH) (Clark, 1973) assumes information dissemination is contemporaneous, while Sequential Information Arrival Hypothesis (SIAH) (Copeland, 1976 and Smirlock and Starks, 1988) suggests the gradual

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[5] *"An efficient market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, the actual price of a security will be a good estimate of its intrinsic value"* (Fama, 1965).

dissemination of information suggesting that a series of intermediate informational equilibria exist in the market. Therefore, an empirical examination of intertemporal and contemporaneous relationships between asset returns and trading volume may provide valuable information about different aspects of the trading dynamics and informational efficiency in financial markets.

The modeling of various financial assets returns volatility continues to be one of the prevailing features in financial markets as it improves major information on the risk pattern involved in the investment and transaction process. By far the most popular approach for describing the stochastic nature of price movements using the statistical models have been proposed in the generalized autoregressive conditional heteroscedasticity (GARCH) literature by Bollerslev (1986), extended from the autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982). The family of ARCH models has been proven to provide a good fit for many financial return series where an autoregressive structure is imposed on the conditional variance. These models allow the volatility shocks to persist over time, and to revert to normal level. These models also capture the propensity of returns to cluster in time and help to explain the non-normality and non-stability of stock return distributions. Many of the proposed ARCH models allow for asymmetric effects of positive and negative shocks on volatility. Models with this feature are often termed “asymmetric” or “leverage” volatility models. While the speeds of adjustment are very high in financial markets, studies using longer time frequencies may fail to capture information included in intraday market movements. Therefore, it may appear that these volatility estimators which utilize intraday returns will be more precise than those that use daily returns. It might also be tempting to conclude that the statistics derived from asymptotic distribution theory should provide good approximations in the high-frequency setting. As a result, there is an apparent tendency toward the use of high-frequency data in the context of modeling time-varying volatility. By extending the ARCH models to include intraday information about trading volume, the modeling of the intraday volatility of asset returns may improve. It is of interest to study various models in order to find out the specifications that provide a good fit as well as a reliable estimation.

Traditionally, most studies that examine the pricing behaviors and modeling of volatility using high-frequency data have primarily either focused on the US or other developed stock markets or have concentrated on foreign exchange markets. More recently, though, there has been a surge of interest among finance scholars in studying the intraday volatility dynamics of emerging stock markets, which play an increasingly important role in global financial markets. However, studies focusing on the emerging financial markets are still rare. In the last twenty years, there have been substantial changes in the degree of openness and stability in most emerging markets. Numerous capital markets in these emerging countries went through intensive reforms leading to the accelerated pace of financial integration in the region and they have grown rapidly due to financial liberalization and technological developments. This phenomenal growth has created new opportunities for international investors who consider these markets as a diversification opportunity and potential sources of high returns, despite additional risks.

Derivative markets are one of the vital complementary components for the development of financial markets in economies that “ought to be present anyhow in the natural evolution of markets”, as put forward by Friedman. Due to recent developments in the financial derivatives markets, these instruments are commonly used for managing various financial risk exposures very efficiently since they allow investors to transfer these risks. In principle, derivatives contribute to a more efficient allocation of capital and cross-border capital flows, create more opportunities for portfolio diversification and facilitate risk transfer, price discovery, and provide more public information (Tsetsekos and Varangis, 1997; Liyina, 2004). In this respect, the growth in derivatives activity over the past thirty years has provided substantial benefits to the market participants[6]. They employ these financial tools to enable both hedging activities and speculative bets on the price movements of underlying assets and in other ways modify the distribution of cash flows from operations significantly at relatively low costs, thereby ensuring better market efficiency. Thus, financial derivatives are essential for the development of efficient capital markets. On account of the rising significance of emerging countries' financial markets, the motivation to employ advanced econometric techniques to examine the intraday behaviors of derivatives and to model their volatility is judiciously justified. Among most exchanges in emerging markets that generated steady expansion in derivative products in recent years, derivatives market in Turkey has achieved remarkable growth.

Turkish capital market finally acquired the long-awaited instruments when it introduced futures trading on its newly established Turkish derivatives market in 2003. As TurkDEX was launched in 2003, trading of its first financial derivatives instrument formally started on February 4, 2005 after a significant improvement in monetary stability conditions. Since then, transaction volume of ISE-30 index futures contract has experienced a stable growth and become the most actively traded

[6] While the notional outstanding value of exchange-traded derivatives financial instrument was $618.3 billions in 1986, it reached $73,137 billions on December, 2009 (Bank of International Settlements (BIS), 2009).

instrument at the TurkDEX[7]. To alleviate the thin trading problem in this newly opened futures market, only the most actively-traded ISE-30 index futures contract is included in the empirical analysis. TurkDEX is of particular interest for empirical work for several reasons. First, the Turkish derivatives market is a rapidly expanding emerging market. According to World Federation of Exchanges' 2008 annual report, the Turkish index futures has experienced the strongest growth and become the third highly traded instrument in Europe, Africa and Middle East[8]. In October 2009, TurkDEX became a member of the Futures Industry Association (FIA)[9], consistent with its objective of becoming more closely integrated with the global derivatives market. Being one of the most important emerging markets, TurkDEX became extremely popular among individual traders, and has drawn great attention from international investors, growing on a global scale as the exchange became the third fastest growing derivatives exchange in the world according to first six months data of FIA in 2009. Thus, TurkDEX futures contracts are regarded as favorable investment vehicles for global investors seeking high return and value investing. Furthermore, compared to other exchanges along financial development, Turkish derivatives market is relatively new as an emerging market. By their nature, since derivatives markets display a high degree of price volatility, leading to unpredictable outcomes, it is vital to investigate the dynamics of volatility in a more accurate way

[7] By the end of 2006, ISE-30 index futures start to dominate the market and this remarkable attempt continue in the following years and at the end of 2009, the trading volume of ISE-30 index futures contract reached TL 310 billion representing 93.03% of the total market value of Turkish derivatives market. The increase in the number of contracts of the ISE-30 index futures was even more stunning – from 164 thousand contracts in 2005 to 65 million contracts in 2009 (TurkDEX).

[8] The growth of Eurex was somewhat slower (9%) but this exchange consolidated its leading position in Europe, while other exchanges in that region (including the second biggest, NYSE Liffe) either stabilized or declined (World Federation of Exchange (WFE), 2008).

[9] Futures Industry Association (FIA) is an association of futures commission merchants, banks and trading advisers operating in the US, European and Asian futures markets. FIA provides information and education on futures markets and trading. It also represents the interest of its members by lobbying regulatory bodies and exchanges.

by means of utilizing high-frequency financial data. However, there has been no research that has been conducted on the intraday characteristics of Turkish derivatives market to the authors' best knowledge. Unlike developed markets, emerging markets might propose a completely different conclusion from the existing literature; together with the possibility of unique findings along the way, this study will be pertinent to both practitioners and academicians by giving them an overall outlook of the intraday behavior of the Turkish derivatives market.

The purpose of this study is to provide an initial understanding of the microstructure of the ISE-30 index futures by examining the intraday return volatility process with the use of GARCH models and its various extensions with a key objective of finding the finest measure for identifying volatility persistence as well as highlighting the impact of the trading volume on the volatility specifications. Further, it will assist in exploring the intraday trading patterns of ISE-30 index futures returns, volatility and trading volume. As financial markets represent high speeds of adjustment, studies employing low frequency data may fail to acquire information contained in intraday market movements. The data set in this study obtained from Matriks Databases[10] contains tick-by-tick transaction data of ISE-30 index futures traded in TurkDEX to mitigate this problem. Using the data set, 15-minute time interval subsequences are constructed, since such a time interval is large enough for new information to be incorporated into futures prices and also sufficient for intraday futures price analysis. To examine the stability of the results, the data set is divided into pre- and post-extension periods consistent with its extended trading hours after September 7, 2007. This research addresses main issues concerning ISE-30 index futures following its two years inception in TurkDEX.

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[10] Matriks is a licensed data dissemination vendor located in Turkey. It provides data and information on global financial markets as well as selected macroeconomic indicators.

This paper contributes to the existing microstructure literature, since it represents the first detailed documented examination of intraday trading patterns behavior of ISE-30 index futures in the Turkish derivatives market, to the best of author's knowledge. While previous studies found that derivatives in emerging markets have a far stronger tendency to rise and fall together, it is of significance to determine whether the trading patterns of Turkish derivatives market are different from those of other markets.

Another possible contribution of this paper is the comprehensive analysis of characteristics of high-frequency series and intraday volatility dynamics of the ISE-30 index futures contract using 15-minute time interval subsequences. The contribution is best appreciated in the context that the empirical distribution of the intraday return is heavy tailed and more peaked around the center. Therefore, alternative distributions possessing such characteristics have been proposed to better account for the deviations from normality in the conditional distributions of returns. It is well known that various GARCH models provide consistent volatility filters for the characteristic of conditionally heteroskedastic data. Since symmetric GARCH model cannot capture the asymmetric response of volatility to news, to capture potential 'Leverage effect', Nelson's (1991) Exponential GARCH (EGARCH) model and the Threshold GARCH (TGARCH) model of Glosten *et al.* (1993) will be also estimated. These models will be compared in order to see which are better in modeling ISE-30 index futures volatility. To add robustness and incorporate innovations to the analysis, each of the GARCH models will be applied under different statistical distributions, comparing the Gaussian distribution to the generalized error distributions (GED). To accommodate the tail thickness and time variation in futures return distribution, a conditional fat-tailed density (GED) would be more appropriate for modeling the pattern of intraday returns.

Futures trading activity, proxied by trading volume, is another important determinant of futures prices volatility. Since trading volume represents the gross market sentiment of both informed and uninformed traders, including trading volume in each GARCH specifications may shed further light on the information asymmetry and volatility clustering in the market (also see Epps and Epps, 1976; Lamoureux and Lastrapes, 1990), which carry important implications for market efficiency. Regarding to the relatively new Turkish derivatives market, trading volume is initially very thin. As Tauchen and Pitts (1983) suggested, in thinly traded and highly volatile emerging markets, prices may deviate substantially from fundamentals due to infrequent trading and limited information flows. When trading volume increases in the market, more information would be available which improve market transparency, reduce uncertainty and market volatility[11]. Also, the extent of noise is expected to be relatively high in emerging markets, with the implication that there is a weaker relationship between trading volume and volatility for emerging markets, which is supported by the Sequential Information Arrival Hypothesis of Copeland (1976) and Jennings *et al.* (1981). Informed traders tend to give rise to the speculative trading activity and increase volatility, decreasing the liquidity of

[11] In emerging markets, decrease in volatility leads to an increase in trades, and prices are adjusted through speculative trading. In many younger markets, transactions are made through a broker and brokers collect and process information from market sources after that passed them on to a trader. As is the case in emerging markets, informed traders can lead to considerable losses on the part of market makers. Therefore, the incentive to market making is decreased and will lead to high spreads to avoid losing money to informed traders. Because there is a well-established literature on the inverse relation between volume and spreads (Abhyankar *et al.*, 1997; Dey and Radhakrishna, 2007; and Cai *et al.*, 2004), it makes sense that when there is no arrival of new information to all market traders, trading will decrease and large shifts in prices might occur at the same time. Thus, in inefficient markets, trading volume is expected to drop, implying a negative relation between information and volatility of returns (Girard and Omran, 2009).

emerging markets which is also a feature of an inefficient trading system and, to some extent, of inefficiency in the market.

The final contribution of this study is that it uses a very comprehensive data set ranging from January 4, 2007 through March 21, 2008, which consists of 2.5 million observations. The use of an extensive data set better characterizes the volatility process by examining the market over a wider range of conditions and a broader market base. The development of intraday time intervals stimulates broad and rigorous empirical investigations of a wide range of issues in financial markets by facilitating a deeper understanding of derivatives market activity. High-frequency data can be used to shift the research focus from aggregate market reaction to individual investors' reactions. By using high-frequency data, it is possible to examine the behavior of individual investors contemporaneously as they trade, rather than analyzing the behavior of investors at the end of the day, week or month. Understanding intraday regularities and price volatility in emerging markets would be beneficial for investors, market participants, regulators and researchers as these markets might exhibit characteristics different from those observed and well documented in developed markets. It can provide significant opportunities for investors to identify the optimum times of the day to trade. Investors are generally concerned about how time-varying volatility affects the pricing and hedging of derivatives since a large adverse price fluctuation may occur during trading. Excessive stock market volatility disrupts the functioning of financial system and harms the economy. It is vital for policy makers and enforcers to better understand market events, in order to formulate and implement effective regulation and choose efficient trading systems. Changes in market rules or regularities may be necessary to increase the stability of the market in a period of excessive volatility.

The remainder of this research is organized as follows. Section 2 presents the theoretical foundation for the analyses conducted in this research and contains the literature review. Section 3 gives background information about derivatives market and brief information about Turkish Derivatives Exchange and discusses the performance of ISE-30 index futures contract used in the analysis. Section 4 provides definition of important concepts about pre- and post-estimation analysis and reviews the theoretical background for conditional volatility models. Section 5 describes the data and examines the distributional properties of 15-minute index futures series in Turkey. The findings in the fifth section will help in determining the appropriate methodology, to be presented in the following section. This rationale comes from the fact that the subsequently employed methodology will rely heavily on the findings regarding intraday return distribution characteristics. Section 6 presents the time-varying volatility models to be applied to the 15-minute ISE-30 index futures contract and describes the performance of these models with and without including trading volume as a proxy for a stochastic process of information arrival. Estimates of the degree of volatility persistence under various distributions are contrasted to the theoretical aggregation results. Section 7 characterizes the intraday trading pattern of the ISE-30 index futures series in 15-minute intervals. Finally, a summary of the results, possible extensions to the research and some implications for decision makers are provided in the concluding section.

CHAPTER 2

LITERATURE REVIEW

2.1 Theoretical Base

Although finance literature has focused much attention on the empirical evidence of intraday dynamics, few papers attempt to explain intraday pattern from a theoretical perspective. The motivation for much of the published literature is the search for evidence to support the microstructural hypothesis regarding stylized features of financial time series studied by many scholars.

Information-based model has recently been proposed as one of the possible explanations for the pattern. French and Roll (1986) were the early pioneers studying the information effects in the US markets. They classified the volatilities in securities market in accordance with public information, private information and noise. French and Roll developed formal hypotheses on the nature and timing of information by using daily opening and closing prices, and by comparing volatility around holidays to non-holiday volatility. They determined that the higher variance during trading hours is caused by differences in the flow of information during trading versus non-trading hours. Amihud and Mendelson (1987) and Stoll and Whaley (1990) investigated daily return variance for New York Stock Exchange (NYSE) stocks and found that open-to-open return volatility was significantly greater than close-to-close variance. Amihud and Mendelson (1987) attributed the higher variances at the market opening effect to “the trading mechanism” used on the NYSE, whereas Stoll and Whaley (1990) argued that it might also be caused by market participants trading on private information. In the following article, however, Amihud and Mendelson (1991) pointed out the higher opening price volatility is primarily affected by the information rather than to differences in trading mechanisms and suggested that the noisiness of opening prices may well be due to the large amount of “unprocessed” information that had accumulated overnight before the market opened rather than to the call auction opening procedure. Miller (1989) claimed that the increase in prices at the beginning of the day can be attributed to a specialists’ moderating behavior, that is, stock prices only partially adjust to information revealed while the markets are closed. He also suggested that a specialists’ behavior produces high returns at the end of the day. However, this argument fails to support for the U-shaped patterns in stock markets that have no specialist systems.

Admati and Pfleiderer (1988) seek to clarify the intraday patterns observed by Wood *et al.* (1985), Harris (1986), and others with a game-theoretic model with three types of traders; informed traders, discretionary liquidity traders and nondiscretionary traders. Informed traders have information on the price of the security one period before it is publicly released. These traders increase price volatility in the periods in which they trade and decrease volatility in the following periods. Discretionary liquidity traders who must trade to satisfy their unique liquidity demands choose specific periods to trade during the day on the basis of trading costs. However, nondiscretionary traders must trade at a given time during the day regardless of cost.

Admati and Pfleiderer (1988) developed an asymmetric information model to explain the strategy trading behavior of informed and liquidity (uninformed) traders and the impact of their trading on volatility and trading volume. Their theory was based on an assumption that liquidity traders prefer to trade when the market is thick to minimize trading costs, while informed traders tend to trade when there is more noise trading to maximize their profit. When the level of noise trading is high, the informed traders can easily camouflage their trades. In equilibrium, all discretionary traders choose to trade at the same time of the day, while this pooling of trades attracts informed traders. This clustering of trade implies more information to be released during whichever part of the day is favored by noise traders. The important consequence was that the trading was concentrated at the open and close of the trading day consisting of the previous empirical evidence on intraday U-shaped patterns for trading volume and returns.

Using an information-based model, Foster and Viswanathan (1990) employed a similar game-theory model to explain trading patterns of volume, returns volatility and adverse selection costs across weekdays, as well as intraday patterns and contended that information is accumulated during non-trading periods. The crucial assumption of their model is that an informed trader has the greatest advantage when the market first opens. This advantage is reduced through time by public information and the market makers inferences through the changes in the order flow. However, contrary to Admati and Pfleiderer, Foster and Viswanathan maintained that periods of high volume and high volatility need not move together.

Easley and O’Hara (1992) pursue an idea that timing of trades is related to the existence of new information. In their model, traders learn both from a trade and a lack of trade because each may be correlated with the properties of the underlying information structure. Therefore, trades convey signals of the existence of any new information and the lack of trade provides signal of the absence of new information. More generally, the receipt of new information may cause informed traders to trade more frequently, and hence their presence may quickly be ascertained by observing high level of trading volume (Easley and O'Hara, 1987). Thus, price changes will be more sensitive to the order flow movements when trading volume and trading costs are high.

As an alternative approach to modeling intraday patterns, Brock and Kleidon (1992) extended Merton' (1971) continuous trade portfolio model to allow for transaction costs and periodic market closures. They derived a market maker power theory to show that traders rebalance their portfolio in consequence of the nature of liquidity demand causing larger bid-ask spreads at the open and close as well as observed increases in volatility and trading volume. Thus, their model is able to account for the concurrence of U-shaped intraday pattern in volatility and volume. Following the insight of Brock and Kleidon (1992), Gerety and Mulherin (1992) indicated that investors are transferring risk when hedging their positions while market is closed. Therefore, the volume at the end of the day should be closely related to the expected overnight volatility. Also, the trading activity at the opening is positively related to both expected and unexpected overnight volatility which support both risk sharing motives and the asymmetric information model.

Slezak (1994) proposed a theoretical framework that market closures delay the resolution of uncertainties, which imposes excess risk on the informed traders[12], thus

[12] Uninformed risk is generated from two sources. The one is the arrival of future news and the other is the imperfect inference of current news, while informed risk generates from only the arrival of

giving a motivation to trade before the market close in order to transfer the risk to noise traders. When the market reopens, those who have not been able to trade overnight trade according to the information revealed during the market closure.

Hong and Wang (2000) presented their theoretical models and addressed how market closures affects investors' trading policies and the corresponding return generating process. Their model proposed that volatility varies across the trading day, but they found different intraday volatility patterns between markets with symmetric and asymmetric information. Under the assumption of asymmetric information, the Hong and Wang model produces a U-shaped intraday volatility pattern. However, under the assumption of symmetric information, the model produces a pattern where volatility is highest at the beginning of the trading day, decreases across the day, and reaches the daily volatility low at the end, resembling a monotonically decreasing curve.

Given the state of incomplete explanations for the intraday trading patterns, Kramer (2001) has more recently tried to use behavioral factors rooted in the psychology of depression to clarify why intraday returns may vary in a systematic manner. In exploring this explanation, she found that hourly returns in the morning significantly exceed those in the afternoon across a variety of time periods and datasets, a novel discovery consistent with the behavioral explanation of hourly returns and contradicting the conventionally believed U-shaped pattern for intraday returns.

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future news. Since a closure increases the variance of future news, but not the variance of current news, informed traders' risk increases proportionally more than the risk faced by liquidity traders.

2.2 Empirical Evidences

The availability of the high-frequency financial data has generated a considerable amount of empirical research which offers a further insight in analyzing the price behavior over the course of the trading day. The literature has investigated the features of intraday patterns in trading volume, return volatility and bid-ask spreads for all financial assets, including foreign exchange, equity, and commodity related securities. While the early empirical studies concentrated on the equity market, concentration has been directed in recent years towards intraday regularities in the markets for foreign exchange, financial and commodity futures. Meanwhile, literature based on high-frequency has presented a striking diversity of the intraday process across the several asset categories and market structure. Though some significant differences are identified across this diverse set of assets, the findings are consistent, enabling a variant of the nonlinear time-series models within the stochastic volatility and GARCH classes.

The US and UK stock markets provided the primary evidence of a U-shaped pattern in the intraday return variance. The intraday patterns in returns, volatility, and volume were first documented by Wood *et al.* (1985) and Harris (1986). While Wood *et al.* (1985) examined two periods, 12 months in 1985 and six months in 1971-1972 using an index of one minute interval returns for all NYSE stocks, Harris (1986) investigated the returns of NYSE stocks over 15-minute intervals data from December 1981 to January 1983. The patterns show that returns, volatility and volume are high near the open and close of the trading in the stock market during a day, indicating a U-shaped intraday pattern.

Jain and Joh (1988) reported the heavy trading in the beginning and the ending of the trading day and relatively light trading in the middle of the day for hourly changes in returns and volatility for data on the S&P 500 over a longer period, 1979-1983. They attributed the higher volume at the open to investors trading on information gathered during the night and in the morning before the market opens, while the higher volume at the close was attributed to the investors closing or hedging open positions that they could not monitor or change overnight. McInish and Wood (1988) examined whether the autocorrelations of one-minute index returns is caused by the effects of nonsynchronous trading on intraday indices or by information arrival. They found that autocorrelation is high near the open and close, which reflects a U-shaped intraday pattern in one-minute index returns. Lockwood and Linn (1990) extended previous volatility studies by examining market variance on an hourly basis for the Dow Jones Industrial Average between 1964-1989 periods. The results demonstrated that return volatility falls from the opening hour until early afternoon and rises thereafter and is significantly greater for intraday versus overnight periods, supporting the existence of a U-shaped pattern in the intraday return variances in the US stock market.

Miller (1989) claimed that the day-end effect is caused by the trading mechanism of the UK market and suggested that the day-end effect is caused by specialists who normally set the prices higher at the last trade to defend their position when the market opens on the next trading day. Therefore, he argued that that specialist functions are responsible for the U-shaped patterns.

Recent empirical research on equity markets has confirmed the existence of specific intraday patterns consistent, in some cases, with theoretical predictions. For stocks listed on the NYSE, Foster and Viswanathan (1993) investigated the first half-hour of trading and found empirical support for the prediction that the non-trading period will be accompanied by higher reopening trading volume, volatility and the adverse selection costs, a component of the bid-ask spread. The adverse selection and informed trading models predicted that volatility, spreads and volume are simultaneously elevated after the lunchtime closure as a result of adverse selection and higher price uncertainty. This result is not consistent with the Admati and Pfleiderer (1988) model that predicts that trading costs are low when volume and return volatility are high.

Also, McInish and Wood (1992) and Chan *et al.* (1995) investigated the intraday pattern of bid-ask spreads on the NYSE and the Nasdaq, respectively. McInish and Wood (1992) indicated that the differences in bid-ask spreads over the trading day can be explained in terms of four classes of determinants, namely; activity, risk, information and competition. They not only found that the spread is inversely related to the number of transactions in a given time period, the number of shares per trade and competition from regional exchanges, but also found that the bid-ask spreads are directly related to cross-section risk, time-series risk during the trading day, as well as abnormal number of trades. Further, they found that the bid-ask spread for NYSE stocks exhibited a crude reverse J-shaped pattern with higher spreads around the opening and closing of the day. In contrast, Chan *et al.* (1995) identified that the bid-ask spread for Nasdaq stocks displayed a distinctively different pattern throughout the day, with wider spreads at the open and narrowing significantly during the final hour of trading. The spread toward the end of the trading day varied from the observed pattern and tended to become L-shaped. Chan *et al.* (1995) examined quoted bid-ask spreads on the Chicago Board Options Exchange (CBOE) which is also a competitive dealer market, and supported the findings of Chan *et al.* (1995). The different patterns of intraday spreads between NYSE and Nasdaq stocks motivate market microstructure researchers to look for possible explanations.

Wei (1992) examined intraday variations in volume, price variability, and the bid-ask spread by employing the information about every transaction for NYSE and American Stock Exchange common stocks during September and October 1987. Trading activity, price variability and the bid-ask spread were the highest in the first hour of the day. In the last hour, trading activity and price variability increase without significant changes in the information and transitory components[13]. These variations demonstrate a U-shaped pattern. The first period results favor the transitory cost explanation contrary to Admati and Pfleiderer's (1989) prediction, while the last period results are possibly explained by investors unwinding their positions before close to avoid overnight risk exposure.

Jang and Lee (1993) identified that trading volume and number of transactions are also higher at the open in NYSE, consistent with the explanation of Jain and Joh (1988) and Foster and Viswanathan (1993). This trading behavior is explained by the higher market activity at the opening is due to overnight information that accumulates during the NYSE nontrading period.

Lee *et al.* (1993) investigated the relationship between the intraday patterns of bid-ask spreads for NYSE stocks and documented a positive correlation between spread and trading volume and a negative correlation between spread and depth. High

[13] Wei (1992) splits the bid-ask spread into an information component (i.e., the asymmetric information cost of trading with informed investors) and a transitory cost component (i.e., order processing costs and inventory holding costs) using the procedures outlined in Glosten and Harris (1988) and Stoll (1989).

volatility is indicative of market uncertainty and possibly an increased presence of informed traders so that a risk-averse specialist will widen the spread. Hence, volatility and spread should be positively correlated. Also, they recognized that the equity specialist is able to adjust both spreads and depths when confronting informed traders, and their results indicated that spreads increase and depths decrease prior to earnings releases. Their analysis demonstrated a reverse U-shaped pattern, supporting an earlier finding of McInish and Wood (1992).

Werner and Kleidon (1996) examined intraday patterns of cross-listed UK stocks using the time interval encompassing the opening market in London until close in the US market. Their focus was to examine the intraday behavior of stocks which were dual traded on the London and US stock exchanges. They found that when the NYSE opens, then high volatility exists in NY for London stocks, but in London no increase in volatility occurs. Consequently, information does not seem to be driving the NYSE volatility. They also indicated that bid-ask spreads narrow towards the close of trading on the competitive dealer market of the London Stock Exchange (LSE). For additional studies on cross-listed securities, see Chan *et al.* (1996), and Moulton and Wei (2005). In contrast to Werner and Kleidon's (1996) finding that British cross-listed stock spreads decline over the first several hours of their trading in US markets, evidencing a separate U-shaped curve in the US, Moulton and Wei (2005) found that British cross-listed stock spreads are significantly lower in the NYSE when the LSE is open. These cross-listed results were suggestive of greater global integration, perhaps due to market structure changes and increased international arbitrage activity during the last decade. Analysis of trading on the LSE, however, demonstrated that despite the availability of cross-listed substitutes on the NYSE, British home market shares retain their U-shaped curve, suggesting that the home and cross- listing markets are not fully integrated.

Atkins and Basu (1995) analyzed the time pattern of public announcements focusing on the periods after the market closes trading hours and found that public information also appears to have a significant effect on the U-shaped pattern of volume for 400 NYSE stocks. This indicated that the large volume at the beginning of the day could be the result of the aggregate amount of new information that becomes known overnight.

Chung *et al.* (1999) reported an alternative explanation for the intraday pattern of spreads on 144 stocks of NYSE. The study found that competition among limit-order traders is lower during the early and late hours of trading than during midday, and indicated that the observed intraday pattern of NYSE spreads mirrors intraday variation in limit-order competition. Based on this finding, they concluded that the U-shaped intraday pattern of NYSE spreads is largely determined by limit orders placed by outsiders rather than by specialists' quotes.

The availability of quote and transaction data has led to the extension of work on intradaily seasonalities in other national exchanges. McInish and Wood (1990) detected a similar U-shaped pattern for returns and volume of the stocks traded on the Toronto Stock Exchange. Niemeyer and Sandas (1995) and Aitken *et al.* (1995a) provided related evidence of intraday regularities on Stockholm and the Australian trading system. Aitken *et al.* (1995a) found that intraday volume on the Australian Stock Exchange (ASX) rises in the first hour of trading, declines through to the middle of the day, and then rises in the last two hours of the day, indicating a similar U-shaped pattern for returns. Also, they (1995b) documented that the bid-ask spread narrows marginally towards the end of the day in Australia. These results were similar to Wei's (1992) study in US suggesting that the information cost component of trading with informed investors is small at the end of the day.

Abhyankar *et al.* (1997) investigated intraday variations in bid-ask spread, trading volume and volatility of returns, using a large sample covering 835 stocks, traded on the LSE during the first quarter of 1991. The return volatility and bid-ask spread were highest at the open, but relatively flat during the trading day, rising slightly at the close of the market. However, in contrast to return volatility and bid-ask spread, trading volume was not U-shaped. It presented a double-humped pattern with highs at 9.30 a.m., and then prior to the close at 4.00 p.m. The results of the statistical tests provided mixed support for the models of Admati and Pfleiderer (1988) and Brock and Kleidon (1992). Ranaldo (2001) empirically analyzed the intraday market liquidity and the intraday market concentration on the Swiss Stock Exchange and exhibited a triple U-shape. He found a U-shaped pattern during the morning and the last half-hour of the trading day, while three peaks characterize the afternoon trading. The first of these two peaks occurs around the pre-opening of the US markets. The second peak coincides with the US market opening.

Chan *et al.* (2000) examined the intraday patterns of trading volume and price volatility for stocks traded on the NYSE and listed on Asia-Pacific and UK exchanges and analyzed whether these patterns are related to public information accumulated overnight. As information about these foreign stocks is more likely to arrive during the NYSE off-trading period than during the trading period, market activity is greater in the morning than the midday. They also found that overnight price movements in local markets affect not only opening returns of foreign stocks, but also returns during the first 30 minutes. This price movement is positively correlated with the price movement of foreign stocks in the morning, with the correlation weakening afterward. This diminishing effect of overnight information on intraday price movements helps explain why price volatility is higher at the open and lower at midday. On the other hand, local price movements cannot explain intraday variations in trading volume. This suggests that the trading volume of foreign stocks on the NYSE is not related to overnight public information. Also, Mian and Adam (2001) investigated the behavior of volatility for intraday equity index returns in the ASX. They found that volatility is high in the early morning, but diminishes through mid-morning, and remains flat during the day. Hence, it was found that volatility of the Australian equities follows an L-shaped curve over the trading day, which differs from the U-shaped pattern commonly documented by previous studies on other markets. Consistent with Chan *et al.* (2000) and Mian and Adam (2001), Brooks *et al.* (2003) proposed and employed a new method for detecting periodicities based on a signal coherence function, which was then tested on a set of 10-minute return intervals, bid-ask spreads, and trading volume of thirty stocks traded on the NYSE. They confirmed previous findings of an inverse J-shaped pattern in spreads and volume through the day. They also demonstrated that such intraday effects dominate day of the week seasonalities in spreads and volumes, while there are virtually no significant periodicities in the returns data.

Recently, Ozenbas *et al.* (2002) examined intraday stock return volatility from 2000 for five markets: the NYSE, Nasdaq, the LSE, Euronext Paris and Deutsche Borse. They observed a U-shaped intraday volatility pattern and returns at the open appear to have the highest volatility of the day while mid-day returns have the lowest volatility. They suggested that the volatility accentuation is attributable to higher spreads, market impact, price discovery and momentum trading and were all linked to market structure.

The empirical literature addressing similar concerns using intraday market data appropriate particularly in the area of the trading of currencies. Ito and Roley (1987) was the first to investigate the effects of surprise components in macroeconomic announcements both from the US and Japan on the intraday movement of the yen/dollar exchange rate. Some early evidence on the cross-sectional patterns in intraday foreign exchange data was provided by Müller *et al.* (1990). Early time-series applications were built on the ARCH model of Engle (1982) to model the dynamics of intraday foreign exchange volatility. Using the GARCH model to specify the heteroskedasticity across intra-daily market segments, Engle *et al.* (1990) explained the causes of volatility clustering in intra-daily yen/dollar exchange rate and also examined the impact of news in the New York market on the time path of per-hour volatility in the Tokyo markets. Baillie and Bollerslev (1990) investigated intraday volatility of exchange rates in the markets using British pounds, German marks, Japanese yen and Swiss francs, recorded on an hourly basis for a six-month period in 1986 and found a consistent intraday volatility pattern in exchange rates. Hourly patterns in volatility were found to be remarkably similar across currencies and appear to be related to the opening and closing of the major world markets. These researchers found large increases in volatility around the open of trading in London and New York and persistent high volatility throughout the morning hours in New York coinciding with the time when regular business hours overlap in London and New York. Using a different sample period, Andersen and Bollerslev (1998) extended Baillie and Bollerslev's study and found similar 24-hour intraday volatility pattern in the deutsche mark/U.S. dollar exchange market. Utilizing hourly JPY-USD exchange rate returns, DeGennaro and Shrieves (1997) added a weekend or vacation indicator variable, as well as the rate of quote arrival, to the conditional variance function. Having controlled for those two potential sources of seasonals in volatility, they found an increase in volatility prior to public announcements and a significant decrease in volatility during and following the hour of news arrival. Cyree *et al.* (2004) replicated the empirical model from Baillie and Bollerslev (1990) to identify the intraday volatility pattern in short-term interest rates and found volatility spikes at the beginning of the business day in Tokyo, London, and New York. They interpreted these results as support for the model by Hong and Wang (2000), which depicts the presence of volatility clusters at the beginning and end of the regular business day, even in the absence of market closures, when most traders are not active during regular non-business hours. Gau (2005) examined the volatility in the Taipei foreign exchange market based on a 4-year sample of 15-minute NTD (New Taiwan dollar)/USD exchange rates from 1996 through 1999. To identify the pattern of intraday volatility in NTD/USD exchange rate changes, the impacts of scheduled macroeconomic news releases in Taiwan and the US are considered. In this study, the periodic GARCH model and the dummy variable approach are combined to capture the more complicated temporal structure of the intraday volatility in the NTD/USD exchange rate changes. The results suggest that the doubly U-shaped pattern associated with separate morning and afternoon sessions due to a lunch break can be partly explained by the scheduled news announcements in the Taipei FX market.

Because of the limited data in most markets, it is natural that main intraday studies are restricted to the US and UK markets only. The recent availability of intraday data in emerging equity markets has also spurred investigations of intraday regularities in diverse institutional settings. Hence, similar patterns have also been explored in some studies on emerging markets, particularly in the Asian stock exchanges that encompass two trading sessions during a day. Instead of a U-shaped structure, a double U-shaped pattern is observed in some of the Asian (Hong Kong, Japanese) stock markets. This result has been attributed to the fact that the markets have two daily trading sessions, separated by a lunch break. To the best of authors' knowledge, Mok's (1989) work is the first intra daily study which was conducted on Hong Kong market. Mok (1989) found that seasonal patterns in intraday market price changes (1986-1988) were unique and independent of the leading US and London markets. He also found a significant close to close week day seasonal effect in the pre-crash period (1987) due to the non trading period of the week day, coupled with an observation of no intraday variation in returns. Ho and Cheung (1991) examined the distributions of the intraday return data and analyzed the existence of both interday and intraday seasonal pattern in the Hang Seng Index (HSI). They found that intraday data is not normally distributed and the market became more volatile after the stock crash in 1987. Ho *et al.* (1993) extended Ho and Cheung's analysis by examining the price-volume relationship in the Hong Kong stock market using 15-minute interval data on returns and trading volume, covering the period from January 1988 to June 1989. They also found a surge in the trading volume in the last 15-minutes of the morning trading session and at the end of the trading day. They also pointed out a significantly positive relation between the trading volume and the absolute value of returns. A significant causality runs from return to volume unidirectionally. They concluded that volume does not seem to hold any information relevant to forecasting stock returns.

Amihud and Mendelson (1991) examined the Japanese market, which also has two trading sessions. Each session is governed by the call auction for the opening and followed by a continuous trading session till close. They found that the morning open-to-open volatility is higher than afternoon open-to-open volatility, concluding that this pattern is caused by the preceding long period of non-trading rather than the trading mechanism. It is also consistent with Choe and Shin's (1993) findings in the Korea Stock Exchange (KSE) that the close-to-close volatility is higher when the market closes in a continuous trading system than when the market closes in a call auction system. Chang *et al.* (1993) analyzed intraday returns and volatilities for the Tokyo Stock Exchange (TSE), a value-weighted index of shares traded on the TSE. Similarly rather than a single U-shaped pattern for risk and returns observed on US exchanges, they found a double U-shaped pattern corresponding to the two trading sessions of the TSE. Consistent to that reported for the TSE, Cheung *et al.* (1994) also reported a double U-shaped volatility pattern for 15-minute intervals using the HSI for the period April 1986 to December 1990. The double U-shaped pattern is reflective of the two daily trading sessions on the Stock Exchange of Hong Kong (SEHK) during their period of investigation (10:00–12:30 and 14:30–15:30), similar to that reported for the TSE. Using a slightly larger sample of 40 stocks, 25 of which trade on the LSE, the authors show that the cross-listed subsample has lower open-to-open versus close-to-close variance than the purely Hong Kong traded subsample. This evidence is consistent with the asymmetric information hypothesis because fewer non-trading hours for the cross-listed stocks mean that less information is accumulated by the start of next day's trading.

Lehmann and Modest (1994) and Hamao and Hasbrouck (1995) investigated the intertemporal behavior of the market microstructure on the TSE. Lehmann and

Modest (1994) analyzed the size of the bid–ask spread and its cross-sectional and intraday stability and reported U-shape intraday patterns in bid-ask spreads, return volatility, and trading volume. Hamao and Hasbrouck (1995) examined the properties of intraday trades and quotes for individual stocks on the TSE. They found evidence consistent with asymmetric information effects within the limit-order book. Similar to the findings of Lehmann and Modest (1994) in the TSE, Chan *et al.* (2001) used the transactions data on thirty three constituent stocks of the HSI in the SEHK and found that the return volatility and price volatility are the largest in the first trading section in the morning. These volatilities also have a spike in the first trading section after the lunch break. Thus, the return volatility in these two sections would be affected by the arrival of information during the close of the exchange. On the other hand, the price volatility is based solely on the transaction prices during each of the sections. In contrast to the finding on trading volume by Lehmann and Modest (1994) in Japan, they observed that trading volume in the afternoon sections is greater than that in the morning sections. The trading volume in the afternoon sections increases towards the end of the trading day so that the largest trading volume occurs in the last section of the day.

Brockman and Chung (1998) examined interday and intraday liquidity patterns in the SEHK and found that the patterns of the bid-ask spreads also follow a U-shaped pattern. Brockman and Chung (1999) also investigated inter-temporal and cross-sectional depth patterns on the SEHK. Based on over six million observations, they reported an inverted U-shaped pattern that mirrors the commonly reported pattern. Lam and Tong (1999) analyzed the same stock exchange and found that open-to-open volatility is slightly lower than the close-to-close volatility. Using one-minute interval intraday data, they discovered a hump-shaped volatility both in the morning and afternoon sessions for the Hong Kong market. They attributed the result to the noise traders who tend to cluster when volatility is high. In addition, Ahn and Cheung (1999) studied intraday market depth, and found an inverted U-shape for Hong Kong market. They attributed the narrow depths and larger spread at the open and close to the limit order traders strategy to avoid possible losses from trading with informed traders when adverse selection problem is severe. Their results are consistent with findings in the NYSE by Lee *et al.* (1993).

Examining the 5-minute Nikkei 225 index returns from 1994 through 1997, Andersen *et al.* (2000) found that intra day volatility exhibits a doubly U-shaped pattern associated with the opening and closing of the separate morning and afternoon trading sessions on the TSE. This heightened volatility around the open and close of the two separate trading sessions on the TSE is broadly consistent with the predictions from theoretical market microstructure models based on the strategic interaction of asymmetrically informed agents. Furthermore, the availability of high-frequency data allows for vastly superior and nearly unbiased estimation that characterizes the long-run volatility dynamics. This supports recent results stressing the importance of exploiting high-frequency intraday asset prices in the study of long-run volatility properties of asset returns. Huang *et al.* (2000) documented that opening price are more volatile than the closing prices in Taiwan stock market which they believe is caused by the lack of continuity during the overnight period. Since the extension of trading hours increases price continuity, higher volatility and higher transaction costs during the open and the close should be reduced. Fan and Lai (2006) investigated the effect of the extension of the trading hours of the TSE on the intraday patterns. They suggested that, in both 2000 and 2001, the volatility was highest at the beginning of the day, then falling gradually, but rising again in the last two intervals. The reasons for these patterns at the beginning of the day are due to the information asymmetry and the reason for the end of the intraday pattern is due to the overnight risk. The opening prices are more volatile than the closing prices, which supports the trading halt hypothesis[14] formulated by Huang *et al.* (2000).

Lee *et al.* (2001) extended the literature by examining the relationship between investors' trading behaviors and trading volume during intraday periods. The pivotal contribution of this study was to track the intraday trading behavior of informed and uninformed investors directly using the data of the TSE. Both informed and uninformed investors tend to place more orders at both the market opening and the close. They documented a J-shaped pattern for real orders and a reversed J-shaped pattern for waiting orders, which demonstrate the intraday pattern of the trading volume.

The result of Wood *et al.* (1985) and Harris (1986) echoed by Ding and Lau (2001), who used a sample of 200 stocks from the Singapore Stock Exchange (SSE) and found that the presence of a trading halt in the midday results in two crude U-shaped return patterns. However, in contrast to Block and Kleidon (1992), the trading halt did not cause volume to be unusually high immediately before or after the halt. Trading activity is not high at the beginning of the day but rises dramatically towards the market close. Bid-ask spread and its volatility, on the other hand, are high at market opening but rapidly decline within the first hour with only a marginal increase at market close. Using 5-minute intraday data of the thirty-two most actively trading stocks on SSE for the period of six months prior to, and after, the

[14] The trading halt hypothesis asserts that investors have a higher propensity to trade at the end of the day since they may want to adjust their portfolios given that no trading takes place during the overnight period. Therefore, the desire to trade will in general be stronger and relatively more inelastic at the open and at the close compared to other times during the trading day. This is called trading halt hypothesis.

introduction of this new system in August 2000, Young *et al.* (2002) investigated the impact of the changes on volatility and the price discovery process and found that the pre-trading session significantly reduced opening stock market volatility, therefore helping in the price discovery process and the development of a more efficient and transparent market. The opening vitality in the SSE dropped by over sixty-percent after the introduction of the pre-trading routine. Overall, although an intraday volatility pattern does not relate a higher open volatility to any driving forces, it does reveal the price discovery process and the pattern of the volatility, which provides further evidence to support the results found by using interdaily volatility.

2.2.1 Intraday Studies on Turkish Stock Market

Examining the intra-daily seasonalities of the stock returns on the Turkish Stock Market in the period from 1996 to 1999, Bildik (2001) found that stock return volatility follows a W-shaped pattern over the trading day since there are two trading sessions a day. In addition, volatility was higher at the open and follows an L-shape pattern during the both morning and afternoon sessions. Results indicated that relatively higher closing prices are not corrected by the market at the opening of the next trading day. Relatively higher mean return and standard deviation at the openings of trading sessions seem to be significantly generated by the accumulated overnight information and the closed market effect (halt of trade). Tezölmez (2000) examined the intraday return and volatility patterns as well as the effect of information release on these. Yüksel (2002) compared volume and volatility relation on the Istanbul Stock Exchange (ISE) before and after the Russian Crisis in 1998. His study provided the first evidence on univariate and joint characteristics of 15-minute common stock trading volume and returns on the ISE. Both average volume and return indicated significant univariate intraday variations, and there existed a positive contemporaneous relation between these variables. Moreover, there was weak evidence that in a GARCH setting, volume had an impact on conditional return volatility. His findings are similar to those of Bildik, but, in this case, for individual stocks. Finally, Küçükkocaoglu (2003) examined the behavior of the intra-daily stock returns and day-end stock price manipulation in the ISE. Studies of intra-daily returns found that stock prices systematically rise towards the closing minute and the last trade is more often initiated by a buyer. It is likely that a trader in the ISE with a substantial net position in a given day will attempt to enhance his performance by manipulating the closing price, in other words, this trader will try to improve his position by placing the last buy order. In order to test for the closing price manipulation by the traders in the ISE, he used a standard OLS regression model, which looks for the effects of the size of the daily traders net position in twenty-three stocks selected from the ISE National-30 index companies and found that close-end price manipulation through big buyers and big sellers is possible in the ISE.

2.2.2 Recent Intraday Studies in Emerging Markets

In recent studies, Niarchos and Alexakis (2003) investigated whether there are certain stock price patterns during the trading sessions in the Athens Stock Exchange (ASE) and if such patterns exist whether it implies a profitable trading rule. The econometric tests indicated that there are intraday patterns in the ASE. In all cases, statistically significant or not, the stock returns follow a U-shape pattern during the trading session. In an effort to shed additional light on the U-shaped curve, a new procedure for U-shape testing; Panas (2005) observed that minimum or maximum stock prices can occur several times during the day. The objective of his study is to use a generalized beta distribution to examine the intraday behavior of stocks, using closing stock prices for each one-minute interval, using data from ASE. The results are consistent with the intraday U-shaped curves, i.e. the time to first maximum (or minimum) stock prices follows a U-shaped pattern. In addition, potential applications of the generalized beta distribution are discussed and exemplified by analyzing the relationship between herd and U-shaped behaviors. Alexakis and Balios (2008) examined the possibility that stock market microstructure characteristics might affect price formation and volatility in the ASE. They concluded that alterations in the structure and the duration of the trading session did not affect volatility or increase informational efficiency.

Chow *et al.* (2004) analyzed the intraday patterns of trading volume and volatility in relation with the information conveyed by the order flow for the TSE. They found that both order flow and volatility are high at the opening and the close, but the trading volume is high only at the close.

Tian and Guo (2007) investigated the behavior of both the interday and intraday return volatility of the Shanghai Composite Stock Index and found that the open-to-open return variance is consistently greater than the close-to-close variance. Examining the volatility of interday returns and variance ratio tests at five-minute intervals indicated two L-shaped patterns starting with a small hump during both the morning and the afternoon sessions, with the morning session having a much higher interday volatility than the afternoon. This L-shaped interday volatility was supported by the similarly shaped intraday volatility pattern. This result suggested that the high volatility of intraday returns for the market opening is not entirely due to the trading mechanisms but also due to both the accumulated overnight information and the trading halt effect. The five-minute breaks after the auction and blind auction procedures are the two major driving forces which exaggerate the high intraday volatility observed at the market opening. This result is consistent with the previous findings on the Hong Kong market (Lam and Tong, 1999; Tang and Lui, 2002).

Sioud *et al.* (2006) analyzed intradaily and weekly patterns of the bid-ask spread, trading volume and volatility on the Tunisian Stock Exchange, using high-frequency data on order flow and transactions. The trading volume exhibited U-shaped pattern over the continuous session for all days of the week. The observed trading volume pattern may be related to liquidity (halt of trade) or investors' psychological factors. For the bid-ask spread, the results supported an end of the day effect and a weekend effect. Intraday spreads are lowest at the market opening and widen considerably towards the close. At the market opening, the patterns of spread and trading volume were consistent with Admati and Pfleiderer (1988) model which predicts that the clustering of traders takes place when transaction costs are low. At the end of the trading day, they observed an increase of spread and trading volume as predicted by Brock and Kleidon's (1992) model. Finally, they found that volatility is highest at the opening, and decreases thereafter at a constant level, and then rises towards the market close.

2.2.3 Intraday Studies in Futures and Options Markets

Common to all these studies is the finding that market openings and closings have profound effects on market behavior, reflected by relatively higher volatility at both beginning and ending of the typical trading day. The empirical studies on the intraday patterns observed in stock markets have been traced in other financial markets, including the futures and options markets. The availability of intraday price data has allowed for analysis of market volatility within a much shorter time frame than had previously been permitted. Both stock and index futures markets respond similarly to the same information set; thus the similar intraday pattern have been observed in the stock and index futures markets. However, it has also been argued that since the two markets may have different trading microstructures, different patterns in the intraday return volatilities may still exist. The empirical results are consistent with a contagion model, suggested by King and Wadhwani (1990), which indicated that the price behavior in one market is affected by the trading in other related markets because traders in one market draw inferences from observed price movements in other markets. Therefore, the relatively high return variance at the opening of the markets is attributed to public or private information, accumulated during the overnight nontrading period, released to the stock and index futures markets at the same time.

The US and UK provide the primary evidence of patterns in intraday returns on futures markets. According to Neal (1988) and Jordan *et al.* (1988), volume and volatility were highly correlated in soybean futures and both variables had U-shaped intraday patterns. Neal (1988) examined the soybean futures market for the period from 1983 to 1984 and found that U-shaped pattern existed in intraday volume and price volatility. He suggested that his findings were consistent with Admati and Pfleiderer (1988), which specified different reactions by informed and uninformed traders to endogenously generated information. Neal also suggested information gathering pattern as the most plausible explanation of the intraday patterns. Increases in volume and volatility near the opening could be related to overnight information gathering, whereas increases at the close could be attributed to traders' last chances for trading. In the soybean futures market, Jordan *et al.* (1988) also found well-defined U-shaped patterns in returns, variance, trade count and returns autocovariance during the period from 1978 to 1984. They found that the returns variance in the first and last forty-five minute period was more than thirty percent higher than the variance in other periods during the day. They attributed the higher variance at the open of trading to the market's responding to information that arrived overnight. The increase in the variance at the close was attributed to noise trading by scalpers and other trades wishing to close out their positions before the end of the day to avoid holding overnight positions. Further, the autocovarince increased significantly during the day and was least negative at the close. They suggested that this pattern indicated more noise trading at the close. They also showed U-shaped intraday patterns in the number of recorded trades and in the autocorrelation of non-zero price changes.

Lauterbach and Manroe (1989) examined transaction data for the S&P 500 index futures for nine months in 1988 and found that the increased returns in the first half hour of trading at Monday opening were higher than those for other days of the week. This finding was different from that in stock markets, which show a sharp fall on Monday mornings. They also found that the standard deviations of returns showed a familiar U-shaped pattern similar to that of the stock markets. Kawaller *et al.* (1990) analyzed transaction data for the S&P 500 index futures for the fourth quarters of 1984-1986 and found that the volatility of futures price followed a U-shaped pattern consistently each day. This finding was confirmed by Chan *et al.* (1991), who also found that the variances of 5-minute returns on S&P 500 futures between 1984 and 1989 followed a U-shaped pattern within each day.

Ekman (1992) attempted to determine whether intraday patterns existed in S&P 500 index futures for returns, volatility and volume. He examined six years of transaction data (15-minute intervals) from 1983 to 1988. Evidence indicated that the intraday patterns in returns were similar to those in the NYSE index returns, as had been observed by Harris (1986). The intraday patterns in volatility and volume were roughly U-shaped, which was consistent with previously observed patterns in stock markets. However, the means of volatility and volume were found to decline in the last half-hour of trading. The slight downturn in the pattern near the close was partially attributed to a change in information arrival due to the close of the NYSE fifteen minutes prior the close of S&P 500. He suggested that these findings were consistent with information trading explanations for intraday patterns in NYSE data. Since then, many authors have found similar evidence in a host of other futures markets.

Ma *et al.* (1992) and Wang *et al.* (1994) documented U-shaped intraday patterns in bid-ask spreads on the Chicago Mercantile Exchange (CME). Ma *et al.* (1992) investigated the intraday bid-ask spread for Treasury bond, silver, soy beans, and corn futures during 1980 and 1986. Their findings indicated U-shaped pattern in the bid-ask spread during the beginning and ending of the trading day. They implied that the larger bid-ask spread at the beginning and end of the trading day is inconsistent with higher trading volume, which should reduce the spread rather than increase it. They provided the explanations of higher levels of trading noise and information uncertainty during the analyzed period. Furthermore, Wang *et al.* (1994) investigated the intraday relationship of bid-ask spread and price volatility on the S&P 500 index futures and found a U-shaped spread pattern for S&P 500 index futures. Daigler (1997) examined and reported similar results for the behavior of the S&P 500, MMI, and T-bond futures contracts by employing 15-minute and 5-minute time intervals. The confirmation of the U-shape curve for futures contradicts the recent findings of Ederington and Lee (1993) and Ferguson *et al.* (1998), who did not demonstrate the U-shape pattern. These results illustrated that public information does increase volatility and trading activity. This increased volatility and activity at the opening was consistent with Admati and Pfleiderer's asymmetric information model. The U-shape pattern also provided evidence to support the market closure theory of Brock and Kleidon.

Kawaller *et al.* (1994) documented mid-day volatility spikes in Eurodollar and deutsche mark futures markets in the US, suggesting this phenomenon may be related to the close of trading in London. Webb and Smith (1994) provided evidence of mid-day deviation in volatility in Eurodollar futures markets that are similar to those documented in Kawaller *et al.* (1994), but which are not coincident with London's market close. For Webb and Smith, however, these two mid-day volatility spikes were substantially less dramatic than those occurring at the opening and close, and their timing did not coincide precisely with the close of Eurodollar futures trading in London. However, Ederington and Lee (1993) did not find any pattern for Eurodollar, Deutschemark, and Treasury bond futures. Docking *et al.* (1999) applied the methodology of Kawaller *et al.* (1994) in order to explore the existence and robustness of possible mid-day spikes in intraday volatility patterns in Eurodollar and deutsche mark futures markets, over an extended sample period covering nearly seven years from September 1988 through June 1995. Results over this entire period confirmed the volatility patterns documented in Crain and Lee (1995), while also lending support to the existence of mid-day volatility spikes as documented in Kawaller *et al.* (1994). For Eurodollar futures volatility, these mid-day spikes corroborated the results documented in Kawaller *et al.* (1994) and Webb and Smith (1994), whereas the deutsche mark futures volatility results were more similar to the mid-day hump in volatility appearing in Crain and Lee (1995), than the dramatic spike in Kawaller *et al.* (1994).

An extensive survey of the literature on intraday and intraweek seasonalities in stock market indices and futures market contracts up to 1989 was given in Yadav and Pope (1992). In the UK, Yadav and Pope (1992) found the FTSE-100 Index futures contract traded on London International Financial Futures and Options Exchange (LIFFE) tended to experience systematic price rises during the first hour of trading and overnight when the market was closed. For the period 1986-1990, Becker *et al.* (1995) analyzed the intra-day shape of price volatility for the Long Gilt, Short Sterling, and other contracts at LIFFE and found significant deviations from the familiar U-shape observed in equity markets, with price volatility spiking around releases of UK and US macroeconomic announcements.

Contemporaneous volume effects were very significant in the futures equation in Gannon (1994). Modeling the contemporaneous volume effects within a trivariate structural simultaneous system framework was first reported for testing 15-minute volatility transmissions from the Australian index futures to stock market in Gannon (1994). This structure demonstrated similar U-shaped patterns in intraday index futures volatility and volume of trade. However, the U-shaped intraday 15-minute Australian index futures volatility effects were not fully accounted for by volume effects, particularly the post lunchtime market opening effect.

Franses *et al.* (1997) analyzed the volatility transmission and intraday patterns of the Bund futures contract which is traded simultaneously at the LIFFE and at the

Deutsche Termin-Börse. They found the presence of a U-shape pattern on volatility at both exchanges, using the procedure of Lockwood and Linn (1990); decreases from the opening until early afternoon and increases thereafter. Buckle *et al.* (1998) investigated the intraday pattern of returns, volatility, volume and price reversals using data on both the Short Sterling interest rate futures and FTSE-100 stock index futures contract, which are traded on the LIFFE at 5-minute intervals for the period November 1992 to October 1993. For both contracts, the U-shape pattern was found for intraday trading volume and volatility, but these variables were higher at the opening than the close. The finding of low reversals at the opening suggested that the high volatility and volume found at this time is the result of information trading, thus supporting the model of Admati and Pfleiderer (1988). However, the higher volume and volatility at the close is associated with high reversals and therefore cannot be explained by information trading. One possible explanation for the high volume and volatility at the close for futures markets is the existence of scalpers[15] who trade to close out their positions before the market closes. Public information in the form of UK macro-economic announcements was found to augment volume and volatility for both Short Sterling and FTSE-100 index contracts. However, for US announcements, volatility increases whereas volume decreases. This result challenged with Admati and Pfleiderer (1988) who predicted that volume and volatility will move together when there is information trading. Similar results are reported by Gwilym *et al.* (1999) for the intraday behavior of five-minute FTSE-100, Short Sterling and Long Gilt LIFFE futures returns volatility and for the volume Long Gilt contract over the same period. The intraday patterns identified exhibit a U-shaped pattern for both volatility and volume in each series. Additionally, spikes in the volatility pattern of

[15] The scalper is an individual who makes trading in the equities or options and futures market by holding a position for a very short period of time, trying to "scalp" a small profit from each trade by exploiting the bid-ask spread.

each series are attributable to the release of UK and US macroeconomic news, with similar but more muted spikes for volume patterns. Abhyankar *et al.* (1999) examined the intraday patterns in returns, volatility, trading volume and bid-ask spreads for the FTSE-100 futures contract for the period January 1991 to June 1993. They found that while both volume and volatility exhibit U-shaped patterns over the day, movements in the spread tend to follow the opposite pattern. In sharp contrast to the behavior reported in a number of studies of US futures markets, they found high spreads at the open, with a further mild rise towards mid-day, falling thereafter with a particularly sharply drop immediately before market close. As far as consistency with microstructure models is concerned, their results are more supportive of the Brock and Kleidon model than the Admati and Pfleiderer model. Indeed, the general conclusion to emerge from studies examining intraday patterns within a variety of US and UK securities markets are of U-shape patterns for mean returns, volatility and volume.

Unlike the U-shaped patterns in trading volume documented across various overseas stock markets, Stephan and Whaley (1990) reported a distinctly different intraday pattern for call options traded on the CBOE. They found that the options market started at a lower trading level and gradually increased to a higher level of activity about 45 minutes after a market opening and than declined during the mid-day and finally trading volume increased before the close of the underlying market. This was followed by a sharp fall during the close of options trading. Aggarwal and Gruca (1993) found that intraday evidence on options traded on the CBOE was largely consistent with both the strategic trading models and the market closure models. On the CBOE, the rate of option trading rapidly increased in the 10 minutes following the end of trading in the underlying market, but then decreased in the last 5 minutes.

Sheikh and Ronn (1994) analyzed intraday variations in volatility for CBOE options across the trading day. They found that the variance of call and put options returns exhibited a familiar U-shaped pattern found in the underlying market across the trading day. Consistent with Stephan and Whaley (1990), Easley *et al.* (1998) also reported a trading peak 45 minutes from market opening for both call and put options traded on the CBOE. Despite these findings, trading volume peaking after market opening have been documented earlier in the trading day. Mayhew *et al.* (1995) indicated that trading frequency peaked after the first 30 minutes of trading, whilst Chan *et al.* (1995) reported that trading volume peaked as early as 5 minutes after the market opens on the CBOE. The later peaks in trading volume in the options market were attributed to a number of differences. First, unlike underlying stock market of the NYSE, the CBOE does not use a sequential call opening procedure. Second, the competitive dealer structure of the CBOE necessitates traders waiting for the best dealer's quotes to arrive, unlike the NYSE, where traders are provided with only one best quote from the specialist. Chan *et al.* (1995) also found that the trading volume of call options decreased in the last 10 minutes at the CBOE when the underlying market is closed, and the trading volume of put options increased in the last 10 minutes. A plausible explanation for this result is that risk averse investors holding long positions in the underlying market will hedge their overnight exposure by buying put options. In addition, Peterson (1990) found a similar pattern in the volatility on the returns for futures and options markets respectively. He examined whether intraday and day of the week effects exist in options listed on the CBOE for 1983 through 1985. While stock and call options return patterns have relatively low weekend returns and high returns late in the trading day, put options have higher weekend returns compared to those in the trading day.

The observed intraday patterns in trading volume on the CBOE are not only unique to this exchange. Berkman (1993) found a similar pattern for equity call options traded on the European Options Exchange. He indicated that option trading volume was low for the opening half-hour. Thereafter, it peaked for the next two hours of trading and then decreased before increasing to a higher level for the last two hours of trading, although less pronounced than during early trading. Niemeyer (1994) reported a comparable hump-shaped intraday pattern, where options traded on the Stockholm Options and Forwards Exchange took approximately 20 to 30 minutes to reach a peak following the market open.

More recently, Shiyun *et al.* (1999) employed a Markov chain methodology to study the intraday behavior of the Nikkei index futures from January 1993 to December 1994 and found that under the U-shaped trading pattern, the market is more active and the volatilities are higher in the opening and closing hour than those in the other trading hours. Therefore, high volatilities should be more frequently followed by high volatilities at the opening and closing periods than those at the other trading periods. However, unlike the results of most of the other intraday bid-ask spread research, their result of intraday bid-ask spread pattern does not show the well-known U-shaped pattern. Copeland and Jones (2002) extended the research on intraday patterns in the returns, volatility and trade volume of the Korean stock market index and index futures market during 1997 and 1998. Similar patterns to those found previously in the heavily investigated Western markets are observed, despite the differing microstructures, institutional framework and time zones between East and West. Both volume and volatility were found to be consistently higher at the start of the trading day during the crisis, presumably due to a rapid reaction to overnight news.

Bellalah and Derhy (2005) investigated the effects of opening and closing on transactions demand, volume, volatility and the bid-ask spreads of options prices and their underlying assets on the Paris Stock Exchange. They indicated that transactions demand at open and close in options markets and the underlying assets markets were greater than at other times of the day. The study revealed that periodic market closure leads to periodic changes in the demand for transaction services and indicated the presence of an increased demand and less elastic transactions around closure.

Only a limited amount of work has been conducted on the effects of the extended trading of the index futures market on the underlying cash market. Among the extant studies in the latter line of research, Chang *et al.* (1995) conducted a pioneer empirical investigation on price volatility around the last 15 minutes of trading in S&P 500 index futures contracts after the closing of the NYSE. They employed two theoretical models to develop predictions on the behavior of futures markets when the underlying market closes. The contagion model developed by King and Wadhwani (1990) implies that traders in one market draw information from observed price movements in another; hence price movements in one market affect price behavior in other related markets. The model predicts a decline in futures market volatility when the underlying market closes. The strategic trading models developed by Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) imply that informed traders seek to transact during periods when liquidity (uninformed) traders trade in order to minimize execution costs, such as when a market opens or closes. Consistent with these models, Chang *et al.* (1995) revealed that price volatility in S&P 500 index futures was substantially reduced immediately after the underlying market closes, and subsequently increased in the closing minutes of trading. The theories relied on by Chang *et al.* (1995) implied that a similar mini U-shaped pattern in price volatility is expected at the close, as well as the opening of trading on the Hong Kong Futures Exchange (HKFE) following the change in trading hours. However, no such pattern was expected prior to the change in trading hours. This provided a natural control for testing the impact of cash market closure on futures price volatility.

On November 20, 1998, the HKFE extended the trading hours of its HSI futures contracts to commence trading 15 minutes prior to the opening, and continue for 15 minutes after the close of the underlying market, the SEHK. The change in HKFE trading hours also provides an opportunity to examine trading behavior in stock index futures contracts when the underlying market opens. Following Chang *et al.* (1995), several studies were conducted on the HSI futures contracts traded on the HKFE.

Ho and Lee (1998) analyzed the trading pattern of the index futures market in Hong Kong, which continues to trade for 5-15 minutes after the close of the SEHK during April 1993 to March 1997. The behavior of the index futures market in Hong Kong was consistent with the contagion model of King and Wadhwani (1990) in that the close of the SEHK leads to an immediate downturn in the return, volatility, and turnover in the index futures market. However, this contagion effect was short-lived as the own market closure effect of the index futures market itself leads to a rise in the return, volatility, and turnover when the close of the futures market is approaching. Thus, after the SEHK close, their study confirmed the existence of a mini U-shaped trading pattern in volatility and return in the HSIF market during the sample period, which was similar to the findings of Chang *et al.* (1995). The long period of nontrading before morning session also leads to a higher morning volatility and turnover.

Ferguson *et al.’* (1998) study indicated that an extension in trading hours can provide powerful evidence for testing the alternative hypotheses. The early opening reduces the closure period, which increases the ability to trade and decreases nontrading risk and accumulates overnight information. Consequently, the market closure models predict that the relative opening volume should decline after the extension. These models further predict that the shortened closure period should reduce the opening return variability because accumulated overnight information would no longer include information between 9:30 a.m. and 10:00 a.m. (Hong and Wang 2000). Thus, the market closure models predict that the relative opening volume and return variability would decline after the extension. Cheng and Cheng (2000) evaluated whether the longer trading hours of the HSIF market would lead to a change in the volatility in the cash and futures markets. They examined the mean difference between the volatility of the HSIF and HSI before and after the extension of trading hours. They indicated that there is a reduction in volatility as well as in the correlation between the volatilities in the first 15 minutes of trading for both markets after the change. Fong and Frino (2001) examined the impact of the extension of trading hours in HSI futures traded on the HKFE over the period October 1998 to January 1999 and provided evidence of a decline in futures market volatility following the close of the cash market and increase at the close of trade using transaction price based measures of volatility for the HKFE. This provided strong evidence that the intraday pattern in volatility is caused by market closure. Evidence of an elevation in price volatility at the open of trade and increase in price volatility following the opening of the cash market was also provided. Consistent with Chang *et al.* (1995), it was concluded that the change in futures market volatility in response to spot market opening and closure was also influenced by contagion effects.

Tang and Lui (2002) examined the volatility in Hong Kong using both interday and intraday returns at different times of the day and analyzed the wait-to-trade hypothesis using 24-hour interday returns and 15-minute intraday returns on HSI and HSIF. Empirical results indicated that the opening to opening interday variance of HSI was higher than the close to close interday variance on all weekdays except Monday, which was consistent with the results of Amihud and Mendelson (1987) and Stoll and Whaley (1990) on the US market. For HSIF, the opening to opening interday variance was higher than the close to close interday variance on Thursday, and Friday was similar to the results of Choi and Lam (1998) on HSIF. Moreover, the interday variance of both HSI and HSIF was lower at the open and higher at the close on Monday. The consistent results of low open correlation but large open variance on all five weekdays suggested that the large open volatility is mainly caused by noise unrelated to information, supporting Admati and Pfleiderer's (1988) model. This also indicated an explanation on the relatively much larger open intraday variance in the cash market. The large open volatility but low open correlation in the cash and futures markets was the result of the trading activities of both random and discretionary liquidity traders.

In a more recent study, Chan (2005) made a contribution to the existing literature by formulating and testing the public and private information and noise trading hypotheses for the extended trading hour of HSI futures market. The empirical results demonstrated increases in trading volume, reductions in the volatility of futures returns, and insignificant changes in pricing errors occur during the extended

15-minutes opening session. These findings were consistent with the hypothesis that increased private information-based tradings in the futures market occur before the opening of the underlying cash market. However, no significant changes in trading behavior were found for the last 15-minutes closing session during the post-extension period.

Chang *et al.* (2006) investigated the intraday patterns of trading volume, volatility, and spreads and day-of-the-week variations for stock index options traded on the Taiwan Futures Exchange (TAIFEX). They found that trading volume of TAIFEX options display a U-shaped pattern. While the volatility at the market opening is extremely volatile, the volatility quickly levels off for much of the rest of the trading. The bid-ask spreads pattern for TAIFEX options approximately follows a U-shaped pattern with a small hump immediately after 13:00 hours.

CHAPTER 3

BACKGROUND INFORMATION ABOUT DERIVATIVES MARKET

3.1. General Trends in Derivatives Trading

Recent years, there has been an increase in the use of derivatives in the asset management industry. As of the end of 2008, 17.6 billion derivative contracts were traded on exchanges worldwide, which consist of 8.3 billion futures and 9.3 billion option contracts, shown in Table 1.

Table 1: **Global Listed Exchange-Traded Derivatives Volume between 2007 and 2008**

Global Listed Derivatives Volume			
	Jan-Dec 2008	**Jan-Dec 2007**	**% Change**
Futures	8,317,699,090	7,217,729,477	15.2%
Options	9,361,078,147	8,308,902,627	12.7%
Total Volume	17,678,777,203	15,526,632,104	13.7%

Note: Based on the number of futures and options traded and/or cleared by 69 exchanges worldwide.
Source: Futures Industry, 2008

Derivatives trading volume increased 7.8 times and grew even more rapidly than cash markets volumes during times when equity markets were bullish, especially between 2003 and 2007. As indicated in Table 2, the highest growth rate was observed for equity derivatives in which trading volume increased 13.5 times between 1998 and 2008, by which time they accounted for 69% of the derivatives trading volume, against 40% in 1998 (WFE, 2009).

Table 2: **The Growth of Derivatives Trading from 1998 to 2008**

Contribution of existing and new exchanges to the growth of derivatives trading
(millions of contracts traded)

	Equity options	Equity futures	Index options	Index futures	LTIR options	LTIR futures
(1) Volume in 1998	623	-	196	172	75	421
(2) Add. trading 2008/1998: (3) + (4) - (5)	3 745	1 059	3 881	2 114	96	900
(3) Of which ex. already present in 1998	2 541	-	3 613	1 819	108	884
(4) Of which new exchanges	1 204	1 059	268	295	0	20
(5) Of which ex. that exit the market	-	-	-	-	12	4
(6) Volume in 2008: (1) + (2)	4 368	1 059	4 077	2 286	171	1 322
Number of exchanges active in that market						
Number of exchanges in 1998	26	0	47	44	18	29
Number of exchanges in 2008	27	19	30	30	7	16

Source: World Federation of Exchange, (WFE), May 2009

Most of the larger emerging markets that have been increasing the trading volume in recent years kept growing in 2008. Exchanges in China, India, Russia, South Africa, and even Turkey experienced huge increases in trading volume.

3.2. Institutional Details of Trading in TurkDEX

Until recently and prior to the creation of the institutional framework for the operation of the organized derivatives in Turkey, transaction volume on derivatives was limited to financial institutions and companies. Although the commencement of a futures market in Turkey had been planned much earlier, macroeconomic instability, high inflation, and high and volatile interest rates prevented it. From 2002 to 2005, Turkey experienced a remarkable economic growth performance and a sharp reduction in the inflation rate[16]. Together with other factors[17], improved macroeconomic policies have played a significant role in the outstanding macroeconomic performance over the 2002-2005 periods. These improvements in the economy and the growth of the Turkish capital market in general between 2002 and 2005 made a significant contribution to the development of the organized derivatives market in Turkey. While the first gold futures contracts were introduced by Gold Exchange in 1995, the currency futures contracts were introduced by ISE in 2001. However, these futures trading ended in a very short time because of insufficient infrastructure. Later, TurkDEX, the first organized derivatives exchange in Turkey, was established in 2003 and formal trading in futures contracts started on February 4, 2005. Aiming to accelerate the growth of the Turkish financial industry as a whole, TurkDEX created a new link between market participants and the financial markets. Like other emerging derivatives markets, the development of Turkish derivatives market stemmed from the need to self-insure against volatile capital flows and manage financial risk associated with the high volatility of asset prices. With the establishment of the TurkDEX in accordance with Capital Market Law 2499, a variety of standardized products base of financial and commodity instruments were offered for the purpose of contributing to the efficiency of the capital market. Since first futures contracts started to trade in 2005, the TurkDEX has developed to become the trading centre of emerging equity index futures markets. The Futures Industry Association (FIA) publication short-listed TurkDEX as one of the fastest developing exchanges in the derivatives industry.

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[16] During the 2002-2005 periods, real GDP grew very rapidly at an annual average of 7.5%. On the other hand, the inflation rate (percentage change in GNP deflator), which is a rough indicator of macroeconomic instability (see Fischer, 1993) decreased from 55.3% in 2001 to 5.3% in 2005.
[17] Factors such as the virtuous cycle of structural reforms, relatively stable political and external environment, the prudent monetary policies, and improved perspective for EU accession have also contributed to the favorable performance.

The TurkDEX, a self-governing joint stock corporation, was formed and authorized by the Turkish Capital Markets Board to launch the first and only derivatives exchange in Turkey. The company has 11 shareholders and the structure of shareholders is shown in Table 3. It currently has 91 members, 74 of which are brokerage firms and 17 are banks, and all members are the direct clearing members.

Table 3: **Shareholders Structure of TurkDEX**

Shareholder	Percentage
The Union of Chambers and Commodity Exchanges of Turkey	25%
Istanbul Stock Exchange	18%
Izmir Mercantile Exchange	17%
Yapi ve Kredi Bankası A.Ş.	6%
Akbank T.A.Ş.	6%
Vakıf Investment Securities	6%
Türkiye Garanti Bankası A.Ş.	6%
Is Investment Securities	6%
The Association of Capital Market Intermediary Institutions of Turkey	6%
ISE Settlement and Custody Bank	3%
Industrial Development Bank of Turkey	1%

Source: TurkDEX

There is a considerable interest in the potential success of this new market because of its role in price discovery and risk management prospects for the Turkish capital markets. The TurkDEX aims to develop and provide financial instruments to help individuals and institutions to manage their risks effectively against abrupt price swings in volatile business environment. These risk management tools traded in TurkDEX are currency (Euro and US Dollars), interest rate (Turkish Government Bonds for 91 and 365 days, benchmark bonds), stock index (ISE-30 and ISE-100

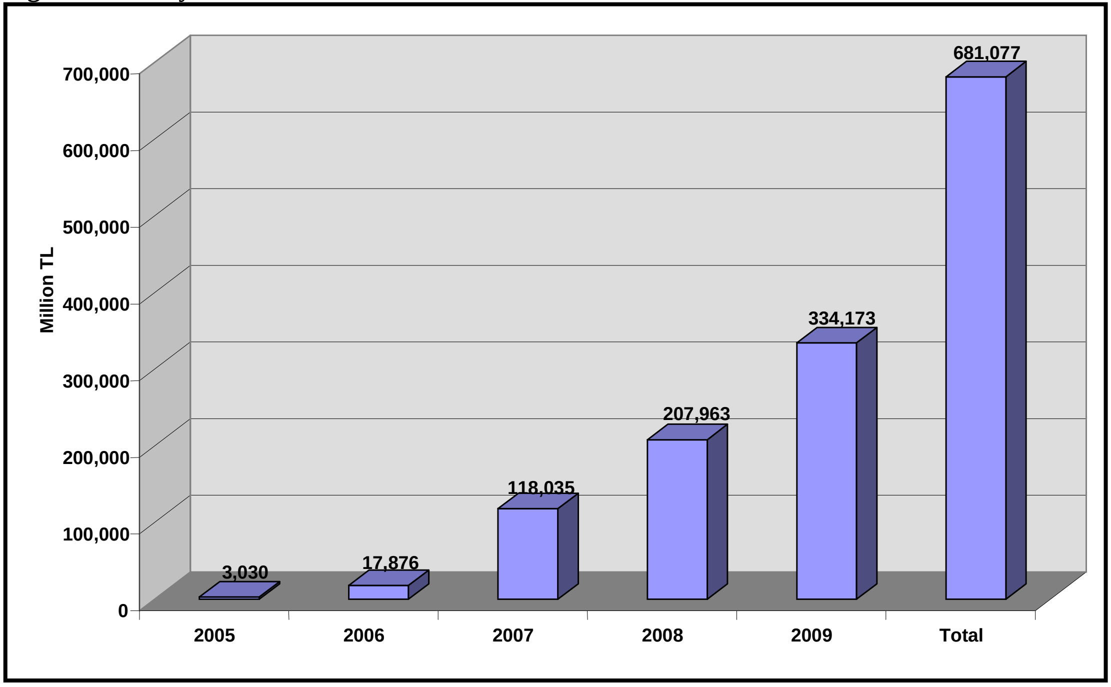
Indices) and commodity (gold, cotton and wheat) future contracts. TurkDEX is dedicated to expanding the trading volume and range of its products by introducing single stock futures and options in the future.

TurkDEX is a fully electronic exchange with remote access. Orders are executed through an automated trading system, known as the TurkDEX Exchange Operations System (TEOS), which is a computerized trading system. This system uses the continuous auction method during normal sessions. In this method, trades are executed based on the prices that form as a result of matching the orders conveyed to the TEOS in accordance with price and time priority rules as prescribed in the Exchange Directive. There are three types of orders that traders can make on the TurkDEX: limit orders, market orders and on close orders. A limit buy (sell) order specifies the maximum (minimum) price which the investor will accept. However, a market order does not specify a price; it is executed at the best possible price available. The buy order is executed at the lowest sell order, the sell order is executed at the highest buy order. Finally, on close order is an order to buy (sell) a stated amount of contracts at the settlement price determined at the end of the day. The use of technology innovation permits an increase in market reliability, providing liquidity and efficiency, and attracting more domestic and international investors. System infrastructure provides an online real-time connection with ISE Settlement and Custody Bank and makes it possible to monitor all orders, transactions, margins and positions on account basis and automatically matches buy and sell orders in accordance with price and time priority basis.

Unlike continuous trading throughout the day, as in the US and UK markets, the Turkish futures market had two trading sessions, the morning session and the afternoon session until October 2009. The futures market initially operated in two-hour sessions during the day; the morning session opened at 10:00 a.m. and closed at 12:00 p.m., whereas the afternoon session opened at 13:00 p.m. and closed at 15:00 p.m. with a one-hour lunch break between 12:00 p.m. and 13:00 p.m.. On 30th December 2005, the opening hours were extended such that the morning session starts at 09:15 a.m. and the afternoon session ends at 16:00 p.m.. On 20th March 2006 the closing time for the afternoon session was further extended to 16:40 p.m.. After September 7, 2007, the trading hours of the day session were extended to begin at 9:30 a.m. and close at 17:10 p.m.. However, the trading hours of TurkDEX were also changed in 2009. The lunch break was lifted and there has been a single session since October 2009, held between 9:15 a.m. and 17:35 p.m..

Figure 1 indicates the yearly transaction volume in the TurkDEX. It can be observed that there is a high interest in futures trading exhibited by a stable uptrend pattern. The total trading volume was almost TL 3 billion at the end of 2005 and witnessed a tremendous increase over the following years, reaching TL 334 billion at the end of 2009. This accelerated growth in the volume of trading in futures contracts has also attracted the foreign investors, whose participation increased from 13% in 2005 to 23% in 2008. The number of contracts traded in the TurkDEX grew from 1.8 million in 2005 to 79.4 million in 2009. According to the Futures Industry Association, the TurkDEX has become the twentieth largest derivatives market in terms of trading volume in the world. Also, the trading performance of derivative instruments has increased, such that the currency futures contracts and the ISE-30 index futures contacts became the ninth and fourteenth most highly traded contracts in the world respectively by the end of 2008.

Figure 1: Yearly Transaction Volume in TurkDEX



Source: TurkDEX

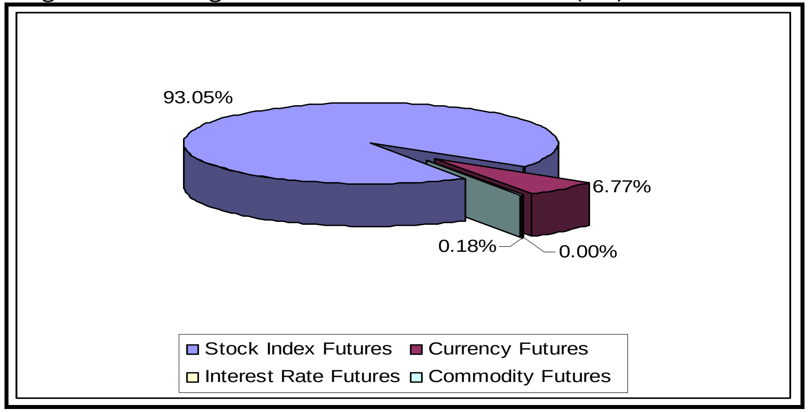
While the trading volume was remarkably high for the currency futures in the first years of operations, trading mostly started shifting towards the ISE-30 index futures in 2006 and after. Table 4 shows the open interest, number of contracts and trading volume statistics in TurkDEX contracts by the end of 2005 and 2009. The trading volume and number of contracts indicate a considerable increase by the end of 2009 when compared with the end of 2005 statistics. As observed from Table 4, the most popular derivative contract of TurkDEX in 2005 was currency futures (90% of the open interest and 76% of the trading volume), followed by the stock index futures with a share of 22.5% trading volume. However, this picture is reversed in the first half of the year 2006 and the stock index futures contracts began to dominate the market with a share of 90.5% trading volume compared to the currency futures (9.4%). At the end of 2008 and throughout 2009, the stock index futures contracts became the market leading instrument in the Turkish index futures markets,

Table 4: Trading Volume, Number of Contracts and Open Interest of the TurkDEX Contracts

Type of Product	2005			2009		
	Trading Volume (TL)	# of contracts	Open Interest	Trading Volume (TL)	# of contracts	Open Interest
Stock Index Futures	658,743,565	164,931	164,931	310,940,738,030	65,399,748	141,241
Currency Futures	2,240,018,049	1,603,797	134,063	22,633,451,061	13,912,680	47,154
Interest Rate Futures	19,945,793	2,814	200	4,805,099	564	0
Commodity Futures	771,525	396	5,890	593,863,892	118,351	581
Total	**2,919,478,932***	**1,771,308***	**140,159**	**334,172,858,081**	**79,431,343**	**188,976**

* Data do not include open positions.
Source: TurkDEX

Figure 2: Trading Value Per Asset Class in 2009 (TL)



Source: TurkDEX

with a market share of 90.51 % and 93.05 % respectively shown in Figure 2. The most popular stock index futures contract in the TurkDEX is the futures contract on ISE-30 index, where the underlying asset is the ISE-30 index. However, trading in interest rate futures and commodity futures is relatively low.

3.2.1 ISE-30 Index Futures Contract

ISE-30 index futures contract is the most actively traded and liquid derivative instrument in the TurkDEX. This contract is of particular importance to investors given that the underlying security represents the stock index for the ISE-30. It is based on thirty actively traded, large capitalization common stocks listed on the ISE. The contracts are cash settled, in the sense that the difference between the traded price of the contract and the closing price of the relevant index is settled between the counter-parties in cash on the expiration day of the contract. Daily settlement is made at the closing of each trading session by taking the weighted average price of all the transactions performed within the last 10 minutes before the closing of the trading session. The contract is cash-settled upon expiration, in which the last settlement price is calculated by an arithmetic average of 10 randomly selected ISE-30 index spot values executed at the ISE within the last 15 minutes of trading in the futures market. Daily price movement limit is ± 15% of the established Base Price for each contract with a different maturity.

The contracts are traded in index points, while the value of the contracts is calculated by dividing the index value by 1,000 and multiplying the quotient by TL 100. The tick size of the ISE-30 futures is 0.025 points, equivalent to TL 2.5. At any point in time, there are six index futures contracts listed, February, April, June, August, October and December, corresponding to the associated expiration months; contracts with three different expiry months nearest to the current month shall be traded concurrently. If December is not one of those three months, an extra contract with an expiration month of December shall be launched. The last trading day is the last day on which the contract may be traded on the exchange. Table 5 displays the main specifications of the ISE-30 index futures contract.

Table 5: **Specifications of the ISE-30 Index Futures Contract**

Main Features of ISE-30 Index Futures Contract	
Underlying asset	ISE-30 Value calculated based on the stock prices of the companies included in ISE National-30 stock price index by using the index's calculation method
Contracts size	Value calculated by dividing the index value by 1.000 and multiplying the quotient by TL 100
Contract Months	February, April, June, August, October and December
Quote Unit	Index points
Last trading day	Last business day of each contract month
Tick value	TL 2.5
Minimum tick	0.025
Initial Margin	TL 700
Maintenance Margin	75% of the initial margin
Daily Price limit	± 15% of the established Base Price for each contract with a different contract month
Settlement method	Cash Settlement

Source: TurkDEX

As of September 2005, trading volume of ISE-30 index futures contract was TL 563 million, accounting for 19.31% of the total market value of the TurkDEX. However, by the end of year 2006, ISE-30 index futures started to dominate the market and the market value of ISE-30 index futures contract became TL 10.4 billion, which represents 60% of the total market value of the Turkish derivatives market. This contract continued to show impressive growth in years 2007, 2008 and 2009 and the trading volume of ISE-30 index futures contract reached TL 310 billion representing 93.03% of the total market value of Turkish derivatives market in 2009.

CHAPTER 4

METHODOLOGY

Building models for high-frequency intraday futures data is certainly more complicated than working with low frequency data because it is well known that high-frequency data is contaminated by market microstructure noise. This study is designed to examine the intraday return volatility process with the use of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models and its various extensions as well as highlighting the impact of the trading volume on the volatility patterns in a very high-frequency setting. Before taking the step of applying conditional volatility models to high-frequency time-series, it should be checked if such a procedure is appropriate. Thus, the main tests that are conducted include Engle's ARCH-LM test and Ljung–Box Portmanteau tests. The former tests whether the data is heteroskedastic, while the latter tests whether volatility clustering is present. After these pre-estimation analyses, suitable GARCH models are used to empirically evaluate the dynamic intraday volatility under different distributions assumptions. In a similar fashion, the results from a conditional volatility specification should be checked to test whether the model is well specified.

4.1 Unit Root Test for Stationary Check

In the past, the economic and finance literature has experienced an explosion of unit root tests for stationarity of time series data since the choice of methodology analysis and modeling series depend on their order of integration. For robustness, two different unit root tests, Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (Kwiatoski *et al.,* 1992), are employed to test the order of integration for each variable. Both tests are applied to determine the stationarity of each time series based on a regression with constant and time trend. They are sensitive towards the lag length included in the regression equation. Hence, for ADF test, the lag length is selected by using Akaike Information Criterion (AIC) while, for KPSS test, the lag length is selected according to Schwert (1989). The null hypothesis of the ADF test claims that the series contain a unit root against the alternative hypothesis of stationary, while the null hypothesis of the KPSS test claims that the series is stationary against the alternative hypothesis of the existence of a unit root. If the unit root hypothesis is rejected and the stationarity hypothesis is failed to be rejected, the series is a stationary process.

The existence of unit root is initially tested using ADF test through the following equation;

$$\Delta R_{i,t} = \alpha + \beta T + \phi R_{i-1,t} + \sum_{j=1}^{k} \gamma_j \Delta R_{i-j,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t} = \ln(P_{i,t} / P_{i-1,t})$ [18], α is the constant term, *T* is the time trend, and β, ϕ, γ_j are parameters to be estimated and k is the number of lags. Because the lag lengths can differ across equations, separate lag length tests should be performed. Moreover, the deterministic time trend might be excluded from the Equation (1). The null and alternative hypothesis for the existence of unit root in series are $H_0 : \phi = 0$, $H_1 : \phi < 0$. When the level stationarity of the series is wanted to test, β has to equal zero; if pure stationarity is the interest, α and β both should equal to zero. The lagged difference terms are included in the specification to control for serial correlation. If the ϕ coefficient from Equation (1) is significantly different from zero, then the series is a stationary process.

The KPSS test is also used to determine whether series are stationary or integrated. Since ADF test is known to lose power as the lag intervals increase, KPSS test has been found to robust for different nonstationary processes (Lee and Schmidt, 1996). The maximum lag order for the test is calculated by using an automatic bandwidth selection routine. As with the ADF test, there are two cases to distinguish between, whether to estimate with and without a linear time trend. The KPSS stationarity test is based on the following regression model,

$$R_{i,t} = \alpha + \beta T + \gamma \sum_{j=1}^{t} x_j + \varepsilon_{i,t} \qquad (2)$$

where *1* and *T* are deterministic components, $\{\varepsilon_{i,t}\} \sim iid\ N(0, \sigma_{i,t}^2)$ and $\varepsilon_{i,t}$ is a stationary error. To test the null hypothesis that the series are trend stationary, only

[18] $R_{i,t}$ is the intraday return on day *t* in interval *i*, and $P_{i,t}$ represents the intraday closing price on day *t* in interval *i* and $P_{i-1,t}$ is the closing price of the preceding interval on day *t*.

γ is equal to zero in the regression. In the case of testing level stationary, $\beta = \gamma = 0$ in Equation (2). Finally, $\alpha = \beta = \gamma = 0$, if pure stationarity of the series is intended to test.

The KPSS test complements the ADF test. The concerns regarding the power of either test can be addressed by comparing the significance of statistics from both tests. The test statistic is as follows:

$$KPSS = \frac{\sum_{t=1}^{T} (\sum_{i=1}^{t} \widehat{\varepsilon_t})^2}{\sigma^2} \tag{3}$$

where ε_t is the residual term, σ^2 is a consistent long run variance and T represents the sample size. If the calculated value of KPSS is large, the null of stationarity for the KPSS test is rejected.

4.2 The Goodness of Fit of the GARCH Model

It is recorded that financial time series display heteroscedastic behavior. Thus, it is necessary to perform a test of autocorrelational conditional variance of heteroscedasticity. In general, there are two methods: namely the ARCH-LM test (Lagrange Multiplier Test) and the Ljung–Box Portmanteau test (Q-statistic) used in testing whether ARCH/GARCH is appropriate for use. In the analysis, a Q-statistic of the standardized residuals, the Q^2-statistic of squares of residuals, and the ARCH-LM test are used to confirm the goodness of fit of the models.

First, if the Q-statistic of the correlogram of residuals and the Q^2-statistic of the correlogram of residuals squared are not autocorrelated, that is, if the null hypothesis cannot be rejected, there is no autocorrelation effect in the residuals/residuals squared items. Second, if in the meantime, according to the ARCH-LM test, the residuals have no ARCH situation, that is, if the null hypothesis cannot be rejected, no ARCH effect exists in the squared residuals. When the conditions fit, it implies that the estimated model can be accepted; otherwise, the estimated results of the fitted model cannot be accepted. The ARCH-LM test and Ljung–Box Portmanteau test are displayed as follows:

4.2.1 ARCH-LM Test

The squared series $\left\{\varepsilon_{i,t}^2\right\}$ can be checked for autoregressive conditional heteroscedasticity using the Lagrange multiplier (LM) test[19]. LM test rests on the null hypothesis that $\left\{\varepsilon_{i,t}\right\}$ is an independently and identically distributed (iid) white noise against the alternative that is an ARCH (q) process. If there is an ARCH (q) effect, the variance equation will be,

$$\begin{aligned} \sigma_{i,t}^2 &= \operatorname{var}(R_{i,t} \left| \psi_{i-1,t}\right.) = E(\varepsilon_{i,t}^2 \left| \psi_{i-1,t}\right.) \\ \sigma_{i,t}^2 &= \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2 \end{aligned} \tag{4}$$

where $\sigma_{i,t}^2$ is the conditional variance and information set, $\psi_{i-1,t}$ includes information available at an interval *i-1* on day *t*, $\varepsilon_{i,t}$ is the white noise disturbance term and q is the lag terms in the model. Before estimating an ARCH model for financial time series, it is necessary to test the presence of ARCH effects in the residuals. If there are no ARCH effects in the residuals, then the ARCH model is unnecessary and misspecified.

[19] ARCH-LM test is proposed by Engle (1982).

The null hypothesis assumes that all the ARCH coefficients are zero,

$$H_0 = \alpha_1 = \alpha_2 = ... = \alpha_q = 0$$

Against the alternative,

$H_1 = \alpha_i > 0$ for at least one $i = 1, 2, ..., q$

The ARCH model with $\sigma_{i,t}^2 = h(z_{i,t}\alpha)$ where h is some differentiable function and $z_{i,t} = (1, \hat{\varepsilon}_{i-1,t}^2, ..., \hat{\varepsilon}_{i-q,t}^2)$ where $\varepsilon_{i,t}$ are the mean-equation residuals and $\alpha = (\alpha_0, \alpha_1, ..., \alpha_q)'$.

The *LM* statistic does not depend on the linear form of the conditional variance function $\sigma_{i,t}^2$ which implies that the test statistic for any specification of $\sigma_{i,t}^2$ depends only on the past squared errors $\left\{\varepsilon_{i-k,t}^2 : j = 1, 2, ..., q\right\}$. *LM* test statistic is based on $LM = TxR^2$ in the regression of the squared residuals on an intercept and lagged values (up to the order of q) of the squared residuals, where T is the number of observations and R^2 is the coefficient of determination for the regression. Under the null hypothesis of no ARCH effects, the LM test statistic has a limiting chi-squared distribution with q degrees of freedom. If the *LM* test for ARCH effects is significant for a time series, one could proceed to estimate an ARCH model and obtain estimates of the time varying volatility $\sigma_{i,t}^2$ based on past history.

4.2.2 LJUNG–BOX Portmanteau Statistics

The Box-Pierce Q-statistic, also known as the Portmanteau test[20], is used to test whether a group of autocorrelation coefficient is significantly different from zero in economic time series. Box and Pierce (1970) proposed the Q-statistic as;

$$Q = T\sum_{k=1}^{s}\hat{\rho}_{\varepsilon,k}^{2} \tag{5}$$

where $\hat{\rho}_{\varepsilon,k}$ is the k^{th} order sample autocorrelation of the residuals and T is the sample size. The size of autocorrelation order (s) is chosen sufficiently large so that the effect of higher-order autocorrelations, which are assumed to approach zero, can be neglected. The null hypothesis is $H_0 = \rho_{\varepsilon,1} = \rho_{\varepsilon,2} = ... = \rho_{\varepsilon,s} = 0$ against the alternative hypothesis $H_a = \rho_{\varepsilon,k} \neq 0$ for some $k \in \{1,...,s\}$. Under the assumption that $\{R_{i,t}\}$ is an iid sequence with certain moment conditions, Q has an asymptotic chi-square distribution with s degrees of freedom. If the calculated value of Q exceeds the tabulated critical value associated with the chosen significance level, the null hypothesis of no significant autocorrelations (uncorrelated residuals) is rejected.

The Q test works poorly even in moderately large samples. In light of this, Ljung and Box[21] (1978) developed the Box-Pierce test for finite sample by modified Q-statistic,

$$Q_m = T(T+2)\sum_{k=1}^{s}(T-k)^{-1}\hat{\rho}_{\varepsilon,k}^{2} \tag{6}$$

---

[20] The test is developed by Box and Pierce (1970).

[21] One of the most well-known statistics for testing the adequacy of a time series model is the Ljung and Box model.

which is known as the Ljung-Box test or Ljung-Box-Pierce test. If the calculated value of Q_m exceeds the critical value of chi-square distribution with s degrees of freedom, then at least one value of $\hat{\rho}_{\varepsilon,k}$ is statistically different from zero at the specified significance level.

Since some of the squared-residual autocorrelations are expected to be significant even if the innovations are iid, a portmanteau test is regarded as a preferable diagnostic tool in discovering nonlinear time series dependencies. McLeod and Li (1983) provide such a test designed exactly as the quadratic counterpart to the Ljung-Box test. Adapting the Ljung-Box test, McLeod and Li test the joint hypothesis $H_0 = \rho_{\varepsilon^2,1} = \rho_{\varepsilon^2,2} = ... = \rho_{\varepsilon^2,k} = 0$ by performing a Q_m test on the squared residuals. The test statistic is,

$$Q_m^2 = T(T+2)\sum_{k=1}^{s}(T-k)^{-1}\hat{\rho}^2_{\varepsilon^2,k} \tag{7}$$

where $\hat{\rho}_{\varepsilon^2,k}$ denotes the k^{th} order sample autocorrelation of the squared residuals. They show that under the null hypothesis of no autocorrelation, Q_m^2 has a chi-square distribution with *k* degrees of freedom.

4.3 Theoretical Models

<u>*4.3.1 ARCH/GARCH Models*</u>

Reliable estimation and forecast of volatility are important for investors and financial institutions where volatility is used to measure risk. In risk management, a risk manager will want to know the probability that the investment value will either appreciate or depreciate in the future. In derivative pricing and trading, an option trader is most interested in the volatility involved in the contract today and the potential change of this volatility in the future life of the contract. In portfolio selection, a portfolio manager needs to adjust the market positions according to the fluctuations of the volatility of underlying assets in order to meet the preset investment goals. In a market-making case, a market maker may want to build a larger bid-ask spread to catch the profits if he believes the market will be more volatile in the future. In general, the study of volatility is valuable to any market participant whether he wants to hedge the risk of volatility or to profit from the increased volatility.

A good candidate for modeling financial time series should represent the properties of the stochastic process. Neither the classical linear Autoregressive (AR) or Autoregressive Moving Average (ARMA) processes nor the nonlinear generalizations can fulfill the task.

Although asset returns, such as stock and exchange rate returns, appear to follow a martingale difference sequence, observation of the high-frequency return plots shows that the pattern of the returns varies across time. A widely observed phenomenon in finance confirming this fact is the *volatility clustering*. This refers to the tendency of large changes in asset prices to be followed by large changes and small changes to be followed by small changes. Asset returns are even not close to being independently and identically distributed. This pattern in the volatility of asset returns was first reported by Mandelbrot[22]. Time-varying volatility and heavy tails found in high-frequency returns data are two of the typical stylized facts associated with financial

[22] Mandelbrot first reported the fundamental differences from the normality: empirical asset return distributions are fat tailed and peaked when compared to normal distribution (i.e. they are leptokurtic).

return series[23]. Linear structural models are inappropriate to take the above-mentioned stylized facts in the financial time series data. Although there are many alternative time series models to predict future volatility, several models were chosen that have been widely used by volatility forecasting studies as benchmark forecasts. These models fix the problems such as thick tails and volatility clustering by assuming autoregressive structure on the conditional second moment, i.e. conditional volatility itself.

The most popular approach of forecasting volatility is the autoregressive conditional heteroskedasticity (ARCH) model originally introduced by Engle (1982). It is one of the pivotal developments in the financial econometrics field and seems to be purposely built for applications in finance. ARCH model states that a shock of an asset return is serially uncorrelated but dependent. The serial dependence of the shock is a simple quadratic function of its lagged values (current returns). The ARCH (q) model expresses the dependent variable $R_{i,t}$ under the information set $\psi_{i-1,t}$ as a linear function of past returns $R_{i-j,t}$ with a parameter vector η_j including the coefficients that display in front of past returns. $\psi_{i-1,t}$ denotes the set of all available information up to the current moment at an interval *i* on day *t*. The ARCH (q) model describes a process in which volatility changes in a particular way and is characterized by the following model:

[23] The term stylized facts is used to describe well-known characteristics or empirical regularities of financial return series. For instance, daily stock index returns display volatility clustering, fat tails and almost no autocorrelation. These three major stylized facts can be explained by the ARCH family of models.

$$
\begin{aligned}
R_{i,t} &= \mu + \sum_{j=1}^{q} \eta_j R_{i-j,t} + \varepsilon_{i,t} \\
\varepsilon_{i,t} &= \upsilon_{i,t}\sigma_{i,t} \qquad \upsilon_{i,t} \sim N(0,1) \\
\sigma_{i,t}^2 &= \mathrm{var}(R_{i,t} \left| \psi_{i-1,t} \right.) = E(\varepsilon_{i,t}^2 \left| \psi_{i-1,t} \right.) \\
\sigma_{i,t}^2 &= \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2
\end{aligned}
\tag{8}
$$

where μ represents the risk premium which results from the econometric models and is time dependent. The stochastic error term $\varepsilon_{i,t}$ is no longer independent but centered and uncorrelated. In ARCH models, the conditional variance of $\varepsilon_{i-k,t}$ is a linear function of the lagged squared error terms. The parameter α_k denotes the strength of the effect of a news shock that occurred k period ago on the current volatility. By assuming a declining effect of news impact, we should expect a declining sequence in values of α_k. The random variable $\upsilon_{i,t}$ is an innovation term which is typically assumed to be iid with mean zero and unit variance. If $\{\upsilon_{i,t}\}$ has the standardized Gaussian distribution (i.e. iid $\upsilon_{i,t} \sim N(0,1)$, the random variable $\varepsilon_{i,t}$ is conditionally normal. The conditional variance σ_t^2 changes over time as a function of past squared errors, $\varepsilon_{i-k,t}$.

The primary advantage of the ARCH specification is that the conditional means and variances can be jointly estimated using traditional econometric methods. Even though the ordinary least squares estimator is unbiased for η in Equation (8), Engle (1982) argues that ARCH estimator is substantially more efficient because it accounts for the conditional heteroscedasticity. However, the ARCH model is only the starting point of the empirical study and relies on a wide range of specification tests. The limitations of the ARCH model include the difficulty to decide on the number of lags (q) of the squared residuals as well as the large variation in the number of lags of the squared errors which are assumed to capture the dependence in the conditional variance. Following the revelation and reporting of practically relevant disadvantages of the ARCH model, numerous extensions of the ARCH specifications have been put forward. In order to overcome these problems, Bollerslev (1986) generalized the ARCH model by including autoregressive terms in the variance equation. This new specification is known as the generalized autoregressive conditional heteroskedasticity (GARCH) model. Although ARCH model is simpler and has been applied to many financial data to model volatility, it often requires many parameters to explain the volatility of return. In particular, the GARCH (p,q) model has been the most popular specification because it is a parsimonious model and often explains strong dependence of volatility of asset returns reasonably well.

Due to its popularity, the GARCH (p,q) specification has widely been used as a proper benchmark to evaluate new types of forecasts. The GARCH (p,q) model which is an extension of the ARCH (q) model can be specified as follows:

$$\begin{aligned} R_{i,t} &= \mu + \sum_{j=1}^{q} \eta_j R_{i-j,t} + \varepsilon_{i,t} \\ \varepsilon_{i,t} &= \upsilon_{i,t}\sigma_{i,t} \qquad \upsilon_{i,t} \sim N(0,1) \\ \sigma_t^2 &= \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2 + \sum_{j=1}^{p} \beta_j \sigma_{i-j,t}^2 \end{aligned} \tag{9}$$

The GARCH (p,q) models are commonly used to capture the volatility clusters of returns and express the conditional variance as a linear function of past information, allowing the conditional heteroskedasticity of returns. α_0 is a constant, α_k is a coefficient that relates the past values of the squared residuals, $\varepsilon_{i-k,t}^2$, to current volatility and β_j is a coefficient that relates current volatility to the volatility of the previous periods, (σ^2_{t-j}) in the GARCH (p,q) model. For the GARCH models expressed in Equation (9), where α_0, α_k and β_j are non-negativity parameters, it is a necessary and sufficient condition that: $\rho = \sum_k \alpha_k + \sum_j \beta_j < 1$ in order for a finite unconditional variance to exist. The sum also provides a measure of the persistence of shocks and controls the speed of mean reversion. The sizes of *arch* and *garch* parameters determine the short and long-run dynamics of the resulting volatility time series (Alexander, 2001). Large GARCH coefficient, β_j, indicates that shocks to conditional variance take a long time to die out, so volatility is “persistent”. Large ARCH coefficient, α_k, means that volatility reacts quite intensely to market movements, and so if α_k is relatively high and β_j is relatively low then volatilities tend to be more “spiky”.

The average number of time periods for the volatility to revert to its long run level is measured by the half life of the volatility shock. The so called half-life of a volatility shock to σ^2_t is defined as $\delta = [\ln(0.5)/\ln(\rho)]$. Obviously, the closer $\sum_k \alpha_k + \sum_j \beta_j$ is to one the longer is the half-life of a volatility shock. Those measures also define the limiting integrated-GARCH (IGARCH) case under $\rho = 1, \delta = \infty$ such that current shocks persist indefinitely in conditioning future variances (Engle and Bollerslev, 1986; Nelson, 1990). However, whilst $\alpha_0 > 0$ and $\alpha_k, \beta_j \geq 0$ may be imposed to ensure non-negativity of the conditional variance, Nelson and Cao (1992) have shown that these inequalities need not hold to ensure a positive variance.

A formal framework for the assessment of GARCH parameter estimates obtained at various frequencies is provided by the theoretical results on temporal aggregation developed by Nelson (1990, 1992), Drost and Nijman (1993) and Drost and Werker (1996). Assuming that the GARCH (1,1) model provides a reasonable approximation of the intraday returns process, the impact of intraday periodicity on GARCH model estimates, and the effectiveness of the periodicity adjustment procedures outlined above in accounting for that periodicity, may be appraised by examining the consistency of estimated and theoretical model properties both prior and subsequent to the application of those periodicity adjustment procedures[24].

A concern with the volatility generation process is that the current volatility is only related to the past values of innovation and volatility spillovers from previous periods. It is likely that variables other than these may contain information relevant for the volatility of stock returns and a possibility is that the incidence of time varying conditional heteroskedasticity could instead be due to an increase in the variability in returns following the arrival of new and irregular information. This is important because the GARCH effects often observed in stocks returns is likely the outcome of the stochastic properties of these factors. Lamoureux and Lastrapes (1990) and Rahman *et al.* (2002), for example, argued that an appealing explanation for the presence of GARCH effects is that the rate of information arrival is the stochastic mixing variable that generates stock returns. For daily, weekly and monthly data, variables such as macroeconomic and company announcements may

[24] While the first-order GARCH model is a widely preferred specification for the modeling of return volatility dynamics, and that specification corresponds to the class of models for which theoretical aggregation results are available, it does not necessarily provide the preferred specification at all intra-day frequencies. Moreover, that serial dependence in conditional mean will in general increase the order of the implied low frequency weak GARCH model beyond the order of the high frequency GARCH (1,1) model. However, Nelson (1990, 1992) establishes general conditions under which first-order GARCH models will, even if misspecified, produce consistent estimates and satisfy the temporal aggregation convergence results given in the text, though it should be noted that those conditions are derived in the absence of any deterministic periodicity in the volatility process.

be major influences. However, for high-frequency intraday data the variables likely to be of most influence relate to trade information. One means of proxying the arrival of this trade information is to introduce the volume of trade into the conditional variance equation. To examine the effect of trading volume, as explanatory variable, on futures returns volatility, the following GARCH(1,1) model is employed.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{i-1,t}^2 + \beta_1 \sigma_{i-1,t}^2 + \psi V_{i,t} \tag{10}$$

where $V_{i,t}$ is the volume of trading at interval *i* on day *t*. Following the argument of Lamoureux and Lastrapes, under the information flow hypothesis[25], the expectation is that the inclusion of trading volume as a proxy for information arrival in the conditional variance equation reduces volatility persistence, the sum $(\alpha_1 + \beta_1)$.

4.3.2 GARCH Models with Distributed Innovations

Numerous studies have found that the empirical distribution of financial asset returns exhibit fatter tails and are more peaked around the center than would be predicted by a Gaussian distribution. Time-varying volatility models with Gaussian distributed innovations are capable of capturing the unconditional non-normality. However, ARCH/GARCH models with conditionally normal errors do not sufficiently capture the leptokurtosis in financial time series. The error term or residual, $\varepsilon_{i,t}$, is conditionally normal if the standardized residual $\hat{\upsilon}_{i,t} = \dfrac{\widehat{\varepsilon_{i,t}}}{\sigma_{i,t}}$ is normally distributed. In the following, $f(z)$ is the standardized density function of the standardized residuals $\{\upsilon_{i,t}\}$. For normal distribution, the density function is represented as;

[25] This hypothesis, introduced by Clark (1973), posits a joint dependence of returns and trading volume on an underlying information flow variable.

$$f(z)=\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{z^2}{2}\right),\quad E\left|\upsilon_{i,t}\right|=\sqrt{2/\pi},\quad \gamma_2=0 \tag{11}$$

The standard normality tests applied to standardized residuals indicated that they are not normal. Thus, these models are able to capture partially the leptokurtosis in the unconditional distribution of asset returns. To model the nonnormality in conditional returns, distributions are needed to employ that accounts for the specific features of the data better than the normal distribution. Thus, alternative distributions possessing such characteristics have been proposed as models for the unconditional distribution of returns. Researchers have proposed alternative distributions like the Student's *t* (Blattberg and Gonedes, 1974) and the generalized error distribution (GED) (Box and Tiao, 1962). Both of these distributions are symmetric and allow excess kurtosis.

The Student's *t*-distribution has only one parameter, d, and its density function can be represented as:

$$\begin{aligned} f(\upsilon;d) &= \frac{\Gamma\left(\frac{d+1}{2}\right)}{\sqrt{\pi d}\,\Gamma\left(\frac{d}{2}\right)}.\left(1+\frac{\upsilon^2}{d}\right)^{-\left(\frac{1+d_{i,t}}{2}\right)} \\ E\left|\upsilon\right| &= \frac{2\Gamma\left(\frac{d+1}{2}\right)\sqrt{d}}{\sqrt{\pi}\,\Gamma\left(\frac{d}{2}\right)(d-1)} \end{aligned} \tag{12}$$

where the degree of freedom $d>2$ controls the tail behavior, υ denotes the random variable with zero mean and unit standard deviation and $\Gamma(.)$ represents the gamma function. This distribution is symmetric around zero and the mean, variance, skewness and excess kurtosis are *0, 1, 0,* and *6/(d-4),* respectively. For the kurtosis, *d* must be larger than 4. It can be shown that the standardized *t(d)* distribution converges to the standard normal distribution as *d* goes to infinity.

Under the assumption of υ approaching Student's *t*-distribution ($\upsilon \sim t(d)$ where *t(d)* refers to zero mean *t* distribution with *d* degrees of freedom and scale parameter equal to one) in the GARCH model, the estimation can be done by quasi maximum likelihood estimation. The combination of linear GARCH model combined with Student's *t*-distribution is called a GARCH-*t* model. In many empirical applications the standardized residuals appear to have fatter tails than the normal distribution. The GARCH-*t* model of Bollerslev (1987) relaxes the assumption of conditional normality by instead assuming that the standardized innovations follow a standardized Student's *t*-distribution. Thus, the GARCH (1,1)-*t* model has been found to outperform the normal GARCH (1,1) model for high frequency stock returns.

Owing to the well-known non-normality of the disturbance term, $\varepsilon_{i,t}$, the distribution is better approximated by GED which has been widely used by financial economists[26]. GED can be represented as:

[26] The generalized error distribution (GED) was initially introduced by Subbotin (1923), and then used by Box and Tiao (1962) to model prior densities in Bayesian estimation and by Nelson (1991) to model the distribution of stock market returns.

$$f(\upsilon;\varsigma)=\frac{\varsigma\exp(-0.5\left|\frac{\upsilon}{\lambda}\right|^{\varsigma})}{\lambda 2^{\left(1+\frac{1}{\varsigma}\right)}\Gamma\left(\frac{1}{\varsigma}\right)}$$

$$E(|\upsilon|)=\frac{\Gamma\frac{2}{\varsigma}}{\Gamma\left(\frac{3}{\varsigma}\right)^{\frac{1}{2}}\Gamma\left(\frac{1}{\varsigma}\right)^{\frac{1}{2}}} \tag{13}$$

$$\gamma_1=\frac{\Gamma\left(\frac{1}{\varsigma}\right)\Gamma\left(\frac{5}{\varsigma}\right)}{\left[\Gamma\left(\frac{3}{\varsigma}\right)\right]^2}$$

where $\varsigma>0,\quad \lambda=\left[\frac{\Gamma\left(\frac{1}{\varsigma}\right)}{2^{\left(\frac{2}{\varsigma}\right)}\Gamma\left(\frac{3}{\varsigma}\right)}\right]^{\frac{1}{2}}$.

Under these conditions, γ_1 represents the kurtosis whereas the GED is leptokurtic when $1<\varsigma<2$. The highest degree of kurtosis that can be generated by the GED is 6 (the Laplace distribution) which is twice the implied kurtosis of the normal distribution, which is (two-thirds) less than can be captured by the Student's t distribution. The unconditional variance exists when υ_t has a GED with scale parameter $\zeta>1$, which determines the thickness of the tails. The GED is leptokurtic when $\zeta<2$. The normal distribution is a special case of the GED ($\zeta=2$).

4.3.3 Models with Asymmetry

Standard GARCH models assume that positive and negative error terms have a symmetric effect on the volatility. In other words, good and bad news have the same effect on the volatility. In practice this assumption is frequently violated, in particular by stock returns, such that the volatility increases more after bad news than after good news. This phenomenon is called *Leverage Effect* and has appeared firstly in Black's (1976) seminal work. He noted that:

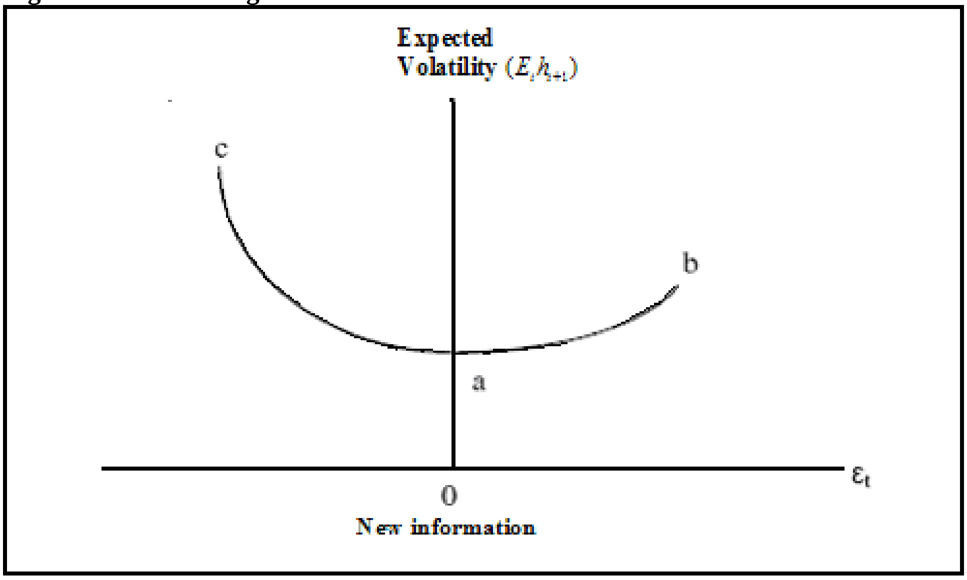
"a drop in the value of the firm will cause a negative return on its stock and will usually increase the leverage of the stock. […] That rise in the debt-equity ratio[27] *will surely mean a rise in the volatility (risk) of the stock".*

Negative returns imply a larger proportion of debt through a reduced market value of the firm, which leads to a higher volatility. The volatility reacts first to larger changes of the market value, nevertheless it is empirically shown that there is a high volatility after smaller changes. On the other hand, Black said nothing about the effect of positive returns on the volatility. Although the positive returns cause smaller increases, they do cause an increase in the volatility. From an empirical point of view, the volatility reacts asymmetrically to the sign of the shocks. The existence of this asymmetric effect implies that a symmetric specification on the conditional variance function as in a conventional GARCH model is theoretically inappropriate. Therefore a number of parameterized extensions of the standard GARCH model have been suggested. The concept of the leverage effect is displayed in Figure 3, where 'new information' is measured by the size of ε_t. If $\varepsilon_t = 0$, expected volatility $(E_t h_{t+1})$ is 0. On the other hand, Figure 3 assumes that any news increases volatility. However, if the news is good (that is ε_t is positive), volatility increases along line ab. If the news is 'bad', volatility increases along line ac. Since line ac is steeper than ab,

[27] Increase in firm's debt to equity ratio leads shareholder, who bear the residual risk of the firm, to perceive their future cash flow stream as being relatively riskier.

a positive ε_t will have a smaller effect on volatility than a negative shock of the same size.

Figure 3: The Leverage Effect



Source: Enders (2004)

The Exponential GARCH (EGARCH) model has been introduced by Nelson (1991) to improve two aspects of the standard GARCH model. The one is that the parameters α and β have to be constrained during the course of the estimation to ensure positivity of the variance process; the other one is that empirical evidence suggests an asymmetric response to volatility shocks. The EGARCH model expresses the conditional variance of a given time series as a nonlinear function of its own past values as well as the past values of standardized innovations. The EGARCH model is represented as

$$
\begin{aligned}
&R_{i,t} = \mu + \sum_{j=1}^{q} \eta_j R_{i-j,t} + \varepsilon_{i,t} \\
&\varepsilon_{i,t} = \upsilon_{i,t}\sigma_{i,t} \qquad \upsilon_{i,t} \sim N(0,1) \\
&\sigma_{i,t}^2 = \operatorname{var}(R_{i,t} \left| \psi_{i-1,t}) = E(\varepsilon_{i,t}^2 \right| \psi_{i-1,t}) \\
&\log(\sigma_{i,t}^2) = \alpha_0 + \sum_{k=1}^{q} \alpha_k g(\upsilon_{i-k,t}) + \sum_{j=1}^{p} \beta_j (\log \sigma_{i-j,t}^2)
\end{aligned} \tag{14}
$$

where $\varepsilon_{i,t} = \sigma_{i,t}\upsilon_{i,t}$ and $g(\upsilon_{i,t}) = \phi_1\upsilon_{i,t} + \phi_2\left[\left|\upsilon_{i,t}\right| - E\left|\upsilon_{i,t}\right|\right]$ are the weighted innovations that model asymmetric effects between positive and negative asset returns, and ϕ_1 and ϕ_2 are constants. The term $\phi_1\upsilon_{i,t}$ determines the sign or asymmetric effect and the term $\phi_2\left[\left|\upsilon_{i,t}\right| - E\left|\upsilon_{i,t}\right|\right]$ determines the magnitude effect. Both $\upsilon_{i,t}$ and $\left|\upsilon_{i,t}\right| - E\left(\left|\upsilon_{i,t}\right|\right)$ are zero mean iid sequences with continuous distribution. Thus, $E\left[g(\upsilon_{i,t})\right] = 0$.

The function $g\left(\upsilon_{i,t}\right)$ can be written as

$$
g(\upsilon_t) = \left\{ \begin{array}{ll} \left(\phi_1 + \phi_2\right)\upsilon_{i,t} - \phi_2 E\left(\left|\upsilon_{i,t}\right|\right) & if\ \upsilon_{i,t} \geq 0 \\ \left(\phi_1 - \phi_2\right)\upsilon_{i,t} - \phi_2 E\left(\left|\upsilon_{i,t}\right|\right) & if\ \upsilon_{i,t} < 0 \end{array} \right. \tag{15}
$$

So that $\phi_1 + \phi_2$ and $\phi_1 - \phi_2$ reflect the asymmetrical response to positive and negative innovations, $\varepsilon_{i-1,t}$. If $\phi_1 < 0$, a positive return shock or surprise will increase volatility less than a negative one of the same magnitude. This is the basic premise of leverage effect.

Since the flow of information into the market is widely unobservable, the trading volume as a proxy for information innovations is used. Systematic variations in trading volume are assumed to be caused only by the arrival of new information into the market. Using the tick by tick data, this proposition can also be tested, which enable to assess the link between trading volume and volatility on an intraday basis. The extended model is given by the following equation;

$$\log(\sigma_{i,t}^2) = \alpha_0 + \sum_{k=1}^{q} \alpha_k \left(\phi_1 \upsilon_{i-k,t} + \phi_2 \left[\left| \upsilon_{i-k,t} \right| - E \left| \upsilon_{i-k,t} \right| \right] \right) + \sum_{j=1}^{p} \beta_j (\log \sigma_{i-j,t}^2) + \psi V_{i,t} \quad (16)$$

The model predicts that $\psi > 0$. The persistence of volatility as measured by β_j should become negligible if $V_{i,t}$, which represents the flow of information, captures the presence of EGARCH in the data.

Following Glosten *et al.* (1993) and Zakoian (1994), another asymmetric GARCH method known as threshold-GARCH (TGARCH) is used to model stock return volatility. Rabemananjara and Zakoian (1993) note that compared with the TGARCH model, EGARCH has the limitation that the effects on volatility of positive innovations relative to negative ones remains fixed over time. Also, EGARCH process implies a linear MA equation on the $(\log(\sigma_{i,t}^2))$ process. Because of the logarithmic form of the conditional variance in EGARCH model, there is no possibility of negative variance. The TGARCH specification captures volatility clustering and asymmetric characteristics. Further, it allows accounting for leptokurtosis and skewness, both of which indicate departure from normality of the data and are regarded as primary characteristics of intraday stock returns. The TGARCH model is expressed as follow

$$
\begin{aligned}
&R_{i,t} = \mu + \sum_{j=1}^{q} \eta_j R_{i-j,t} + \varepsilon_{i,t} \\
&\varepsilon_{i,t} = \upsilon_{i,t}\sigma_{i,t} \qquad \upsilon_{i,t} \sim N(0,1) \\
&\sigma_{i,t}^2 = \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2 + \sum_{j=1}^{p} \beta_j \sigma_{i-j,t}^2 + \sum_{l=1}^{r} \theta_l D_{i-l,t} \varepsilon_{i-l,t}^2
\end{aligned}
\tag{17}
$$

where $R_{i,t}$ is the realized return of the stock, expressed as a random walk process with an error term of mean zero and conditional variance $\sigma_{i,t}^2$. The conditional variance $\sigma_{i,t}^2$ is specified as a function of the mean volatility α_0, $\varepsilon_{i-1,t}^2$ which is the lag of the squared residual from the mean equation providing news about volatility clustering; $\sigma_{i-1,t}^2$ represents the last minutes' forecast variance and finally, $D_{i-1,t}\varepsilon_{i-1,t}^2$ is the term to capture the asymmetry. The potential asymmetry, restricted to a first order effect only, is captured by the use of the dummy variable $D_{i-l,t}$ such that $D_{i,t} = 1$ if $\varepsilon_{i,t} < 0$ and $D_{i,t} = 0$ otherwise. Unlike GARCH model, there are no restrictions on the parameters α_k, β_j and θ_l to ensure non-negativity of the conditional variance. In this model, good news, $\varepsilon_{i-k,t} > 0$ and bad news $\varepsilon_{i-k,t} < 0$ have differential impacts on the conditional variance; good news has an effect of α_k, while bad news has an impact of $\alpha_k + \theta_l$. The TGARCH (p,q,1) specifications thus allows negative shocks to have a greater impact on subsequent volatility if the real constant $\theta_1 > 0$, whilst overall shock persistence is quantified by $\rho = \sum_k \alpha_k + \sum_j \beta_j + (\frac{\theta_1}{2})$ with half-life. If the coefficient θ_i is statistically different from zero, the news impact is asymmetric for the i[th] order. The volatility persistence is measured by β_j and represents the change in the response function of shocks to volatility within 15-minutes intervals. If this value is higher than 1, it indicates that the response function of volatility will be explosive, on the other hand, when the value is lower than unity, this points out that the response of volatility declines over time.

The TGARCH model is extended by taking the differential impact of trading volume on volatility through conditional variance equation. Accordingly, the unexpected price increments in a day, ε_t, will be the sum of a number of intraday price changes. GARCH effects may be explained as a manifestation of time dependence in the rate of evolution of intraday price changes driven by new information arrival. Following earlier studies, intraday trading volume as a proxy for the unobservable new information arrival is used. The model can be represented as follows;

$$\sigma_{i,t}^2 = \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2 + \sum_{j=1}^{p} \beta_j \sigma_{i-j,t}^2 + \sum_{l=1}^{r} \theta_l D_{i-l,t} \varepsilon_{i-l,t}^2 + \psi V_{i,t} \qquad (18)$$

where $V_{i,t}$ is the detrended trading volume. This extended model accounts for potential impact of volume on the volatility of 15-minutes futures returns.

One way to test for leverage is to estimate the TGARCH or EGRACH model and perform a t-test for the null hypothesis $\hat{\theta}_1 = 0$. However, there is a specific diagnostic test that allows you to determine whether there are any remaining leverage effects in residuals. Thus, the $\{\upsilon_{i,t}\}$ sequence consists of each residual divided by its standard deviation. To test for leverage effects, a regression in the following form is estimated;

$$\upsilon_{i,t}^2 = a_0 + a_1 \upsilon_{i-1,t} + a_2 \upsilon_{i-2,t} + \ldots + a_n \upsilon_{i-n,t} \qquad (19)$$

If there are no leverage effects, the squared errors should be uncorrelated with the level of the error terms. Hence, it can be concluded that there are leverage effects if the estimated F for the null hypothesis $a_1 = a_2 = ... = a_n$ exceeds the critical value obtained from F table.

Engle and Ng (1993) developed an alternative method to determine whether positive and negative shocks have different effects on the conditional variance. Let $D_{i-1,t}$ be a dummy variable that is equal to 1 if $\hat{\varepsilon}_{t-1} < 0$ and is equal to 0 if $\hat{\varepsilon}_{t-1} \geq 0$. The test is to determine whether the estimated squared residuals can be predicted using the $\{D_{i-1,t}\}$ sequence. The Sign Bias test uses the regression equation in the following form;

$$\upsilon_{i,t}^2 = a_0 + a_1 D_{i-1,t} + \varepsilon_{1t} \tag{20}$$

where ε_{1t} is a regression residual.

If the t-test indicates that a_1 is statistically different from zero, the sign of the current period shock is helpful in predicting the conditional volatility. To generalize the test, the regression is estimated as follows;

$$\upsilon_t^2 = a_0 + a_1 D_{t-1} + a_2 D_{t-1}\upsilon_{t-1} + a_3(1 - D_{t-1})\upsilon_{t-1} + \varepsilon_{1t} \tag{21}$$

The presence of $D_{t-1}\upsilon_{t-1}$ and $(1 - D_{t-1})\upsilon_{t-1}$ is designed whether the effects of positive and negative shocks also depend on their size. F-statistic can be used to test the null hypothesis $a_1 = a_2 = a_3 = 0$. If there is a leverage effect, a specific form of the TGARCH or EGARCH model can be estimated.

4.4 Post Estimation Analysis

To evaluate the relative fit of the empirical validity of the conditional volatility models and to test whether the GARCH models adequately capture the dependencies in the return data, diagnostic tests, ARCH-LM test and Ljung–Box Portmanteau test, are conducted on the standardized residuals from these models. If a GARCH model has captured volatility clustering, the residuals standardized by their conditional volatility should have no significant ARCH effect left. To test whether there are remaining ARCH effects, Engle's ARCH-LM test is, therefore, applied to the standardized residuals. Just as in the pre-estimation analysis, the autocorrelation function is useful in post-estimation analysis. Ljung–Box Portmanteau test is used whether autocorrelation in the residuals and squared residuals has been successfully removed. The standardized and squared standardized returns should have no remaining autocorrelation if the GARCH models are well specified.

In order to motivate the theoretical developments, the following section describes the important empirical features that pertain to the volatility in the Turkish derivatives market and empirical results with the use of GARCH models and its extensions. The methodology apply equally well to the most actively-traded ISE-30 index futures contract in a high-frequency series.

CHAPTER 5

DATA

This study makes use of intraday transaction data of ISE-30 index futures contract provided by Matriks[28] database and covers the period from January 4, 2007 through March 21, 2008. The period is deliberately chosen in order to eliminate infrequent trading in the early days of the Turkish derivatives market. Each trade is time-stamped to the nearest second, which is ideal for the intraday study. Because of thin trading during parts of a trading day, some minute-by-minute data of the day are not available. The prices are for real-time transaction prices, which are partitioned into 15-minute price intervals using the last price quoted before the end of every 15-minute interval over the trading day[29]. Using the tick-by-tick data set, 15-minute interval subsequences of the futures trading prices are constructed, since such a time interval is large enough for new information to be incorporated into stock prices but also sufficient for intraday stock price analysis (Chang *et al.*, 1995; Abhyankar *et al.*, 1997).

Trading hours of the stock index futures before September 7, 2007 were from 9:15 a.m. to 16:40 p.m. with a one-hour lunch break between 12:00 p.m. and 13:00 p.m., giving a total of 25 fifteen-minute intervals during the trading day, whereas the stock

[28] Matriks is a licensed data dissemination vendor located in Turkey. It provides data and information on global financial markets as well as selected macroeconomic indicators.
[29] The computer program used for this purpose is based on the MATLAB.

index on the ISE traded from 9:30 a.m. to 16:30 p.m. with a two-hour lunch break between 12:00 p.m. and 14:00 p.m. Consecutively, two changes were made to the trading hours on the Turkish Derivatives Exchange. On September 7, 2007, the opening of the market was moved from 9:15 a.m. to 9:30 a.m. and the exchange extended its trading hours by ten minutes. Hence, from September 7, 2007 onwards trading occurred from 9:30 a.m. to 17:10 p.m. with a one-hour lunch break between 12:00 p.m. and 13:00 p.m., which gives a total of 26 fifteen-minute intervals within the trading day, whereas the stock index on the ISE traded from 9:30 a.m. to 17:00 p.m. with a two-hour lunch break between 12:00 p.m. and 14:00 p.m. Thus, there is a 10-minute period in which the cash market is closed but the futures market is still open[30]. The sample period is broken down into two periods: the pre-extension period is from January 4, 2007 to September 7, 2007 and the post-extension period is from September 7, 2007 to March 21, 2008.

As with all asset price analyses, there are some potential problems with data unreliability due to the sheer amount of data being used and the fact that there is considerable noise in the series because of little trade occurring at some of the recorded prices. However, algorithms have been proposed in the literature for eliminating these problems. Zhou (1996) mentioned a simple method to validate data by comparing each quote to the medians of the three preceding and the three subsequent observations and removing it if it is outside a fixed distance from those medians.

[30] Chang *et al.* (1995) examined the effects of the closing of the NYSE on volatility and price changes in the S&P futures market, and concluded that when the NYSE closed, volatility of the futures market exhibited a U-shaped pattern in the 15-minute period.

As an alternative, a procedure[31] is suggested which has given satisfactory results in removing aberrant transaction prices from the sample, as argued below. Sampling transaction prices at 15-minute intervals mitigate the effect of aberrant ticks, but the filter is applied to ensure the transaction prices used are reliable. Let $\{p_i\}_{i=1}^{N}$ be an ordered tick-by-tick price series. The proposed procedure to remove outliers is

$$\left(\left|p_i - \overline{p}_i\right| < 3s_i + \gamma\right) = \begin{cases} \textit{true observation i is kept} \\ \textit{false observation i is removed} \end{cases} \tag{22}$$

where $\overline{p}_i$ and s_i denote the 10% trimmed[32] sample mean and standard deviation respectively of an ordered tick-by-tick price around i, and γ is a granularity parameter controlling for the discreteness of prices. It can be seen that the filter removes ticks that deviate from their tick by 3 standard deviations.

To minimize data errors, the procedure described above is followed and several data filtering rules are applied on the tick-by-tick data[33]. First, a trade is excluded if it is out of sequence, recorded before the open and after the closing time, or has special settlement conditions because it might then be subject to distinct liquidity considerations. Second, quotes recorded outside the regular trading hours are excluded. Third, any observations affected by national or international holidays are removed.

The final sample for ISE-30 index futures used in the subsequent analysis contains 310 trading days realizing a total of 2,542,243 observations, 9,253 of which are immediately discarded since they occur outside the TurkDEX trading day official

[31] This method is suggested by Brownlees and Gallo (2006).
[32] Trimmed mean and standard deviation are calculated by excluding the smallest and biggest observations.
[33] The processes are conducted in STATA.

time spanning from 9:15 a.m. to 16:40 p.m. before September 7, 2007 and 9:30 a.m. to 17:10 p.m. after September 7, 2007. October 11, and December 19, 2007 are dropped from the data because those days were holidays. However, there were no outliers in the sample to be removed after applying the proposed procedure.

Futures contracts usually provide less liquidity when their expiration date is distant. The nearby futures contracts are often the most actively-traded contracts, except for the final settlement day. In order to avoid thin markets and expiration effects close to the expiration date, as in Huang (2004), the futures prices are rolled over into the closest contract when that contract emerges as the most active contract.

For each 15-minute interval, returns are calculated as the logarithm of the last price of the interval minus the logarithm of last price of the previous interval. If there is no trading at the end of the 15-minute period, the closest trading price to the end of the period is the closing value of that 15-minute interval. Intraday returns are calculated for each interval as:

$$\begin{aligned} R_{i,t} = \ln(P_{i,t} / P_{i-1,t}) \qquad & i = 1,2,3....25 \quad \textit{for before September } 7,\, 2007 \\ & i = 1,2,3....26 \quad \textit{for after September } 7,\, 2007 \end{aligned} \tag{23}$$

where $R_{i,t}$ is the intraday return on day *t* in interval *i*, and $P_{i,t}$ represents the intraday closing price on day *t* in interval *i* and $P_{i-1,t}$ is the closing price of the preceding interval on day *t*.

Volatility is measured as the squared returns, $\sigma_{i,t}^2$, which is calculated as follows:

$$\sigma_{i,t}^2 = [\ln(P_{i,t} / P_{i-1,t})]^2 \tag{24}$$

For the first interval ($i = 9:15$ a.m. and $i = 9:30$ a.m. before and after September 7, 2007 respectively), since there is no value for $P_{i-1,t}$ the volatility is calculated as follows:

$$\begin{aligned} \sigma_{i,t}^2 &= [\ln(O_{1,t} / P_{25,t-1})]^2 \quad \text{for before September 7, 2007} \\ \sigma_{i,t}^2 &= [\ln(O_{1,t} / P_{26,t-1})]^2 \quad \text{for after September 7, 2007} \end{aligned} \tag{25}$$

where $O_{1,t}$ represent the intraday opening price on day *t* in the first interval. Volume is computed as the number of shares traded over for each 15-minute interval.

Following Gallant *et al.* (1992), Girard and Biswas (2007), the trading volume series are detrended by regressing the series on a deterministic function of time. To allow for a linear and non-linear trend, the residuals are employed from the quadratic time trend equation given by:

$$\ln vf_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t \tag{26}$$

where $\ln vf_t$ denotes the logarithm of the trading volume of futures contract and *t* and t^2 are linear and quadratic time trends respectively. By the nature of the variable, the volume is non-negative and positively skewed. The logarithmic transformation generates variable with more symmetric distribution. The log transformation also reduces the variances of volume and makes the distribution more stable, which helps the estimation of more parsimonious model with more robust forecasting ability.

5.1 Descriptive Analysis

The descriptive statistics of intraday ISE-30 index futures series are represented in Table 6. The sample average return of $-0.74\text{x}10^{-4}$% appears indistinguishable from zero given the sample standard deviation of 0.85%. The distribution is positively skewed[34], implying that, for 15-minute intervals, large positive returns occur more often than large negative returns. While the distributions of the return series are skewed to the left, volatility and volume series show positive skewness. Moreover, kurtosis[35] is larger than three (normality) for return and volatility series which suggest that the distribution is leptokurtic (i.e., high-peaked and fat-tailed). This leptokurtic character persists despite the removal of extreme spikes from the raw returns data. The observed leptokurtosis may be due to heteroskedasticity in the data, which may be captured with the ARCH/GARCH models discussed later. Also, the Generalized Error distribution (GED) may be appropriate because of significant excess kurtosis and skewness (Arago and Nieto, 2005). However, the kurtosis for trading volume is less than three, which suggests that detrended volume has the platykurtic (flat-topped)[36] distribution. The skewness and kurtosis of the returns fit stylized facts of financial returns reported in most research in finance.

Before fitting any probability distribution model to data, the underlying assumptions of the model need to be verified empirically. Almost all of the popular models of stock returns require that returns are independent random variables, and many also require that they are identically distributed.

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[34] Skewness, is the degree of asymmetry, or departure from symmetry, of a distribution.
[35] The fourth standardized moment which is a measure of flatness or peakedness of a single humped distribution is also called kurtosis.
[36] Platykurtic distribution has thin tails than the normal distribution and the kurtosis is lower than 3.

In order to test the hypothesis of independence, a test of white noise process is employed by applying the Ljung-Box-Pierce Portmanteau test statistics (Q-statistics) for both the standardized and squared standardized residuals. It is asymptotically distributed with chi-square distribution with degrees of freedom equal to the number of autocorrelations. The test statistics for up to 50th order serial correlation (denoted by $Q(50)$ and $Q_s(50)$ respectively) are illustrated in Table 6. From these test statistics, the null hypothesis of white noise is rejected and the results assert that these series are highly significant at virtually any level in the corresponding asymptotic chi-square distribution, suggesting the presence of strong nonlinear dependence in the data. Significant autocorrelations in the volume series have also been found in many earlier studies (see, for example, Gallant *et al.*, 1992; Campbell *et al.*, 1993). This implies that trading activity is autocorrelated and this will manifest itself in GARCH effects. A formal test to check whether a distribution is normal is the Jarque-Bera test. The Jarque-Bera statistics for normality are well beyond the critical value for the chi-square distribution with 2 degrees of freedom. It indicates that the whole series, return, volatility and volume, exhibit significant deviation from the normal distribution, suggesting non-normality at the 1% significance level.

Table 6: Descriptive Statistics of 15-minutes ISE-30 Index Futures Series

Data	Mean	*SD*	Skewness	Kurtosis	*JB*	$Q(50)$	$Q_s(50)$
04.01.2007-21.03.2008							
Return	-0.74x10^{-6}	0.0085	-0.1015	403.44	59.139x10^{6}*	1508.15*	2198.40*
					(0.000)	(0.000)	(0.000)
Volatility	0.73x10^{-4}	0.0015	40.755	1736.16	1110.3x10^{6}*	2198.40*	2207.90*
					(0.000)	(0.000)	(0.000)
Volume	-1.07x10^{-15}	1.2139	0.2216	2.4733	174.79*	61.916	144.597*
					(0.000)	(0.122)	(0.000)
04.01.2007-06.09.2007 (Pre-extension Period)							
Return	0.47x10^{-4}	0.0082	-0.0124	390.42	3.1407x10^{7}*	916.004*	1228.84*
					(0.000)	(0.000)	(0.000)
Volatility	0.68x10^{-4}	0.0013	35.813	1309.8	3.5456x10^{8}*	1228.84*	1230.19*
					(0.000)	(0.000)	(0.000)
Volume	-0.049	1.2395	0.2079	2.5005	87.037*	61.920	108.798*
					(0.000)	(0.120)	(0.000)
07.09.2007-21.03.2008 (Post-extension Period)							
Return	-0.61x10^{-4}	0.089	-0.1883	405.32	2.67x10^{7}*	644.694*	970.397*
					(0.000)	(0.000)	(0.000)
Volatility	0.79x10^{-4}	0.0016	43.720	1921.9	6.02x10^{8}*	970.397*	975.759*
					(0.000)	(0.000)	(0.000)
Volume	0.0062	1.1806	0.2429	2.4169	93.761*	40.218	66.424**
					(0.000)	(0.837)	(0.060)

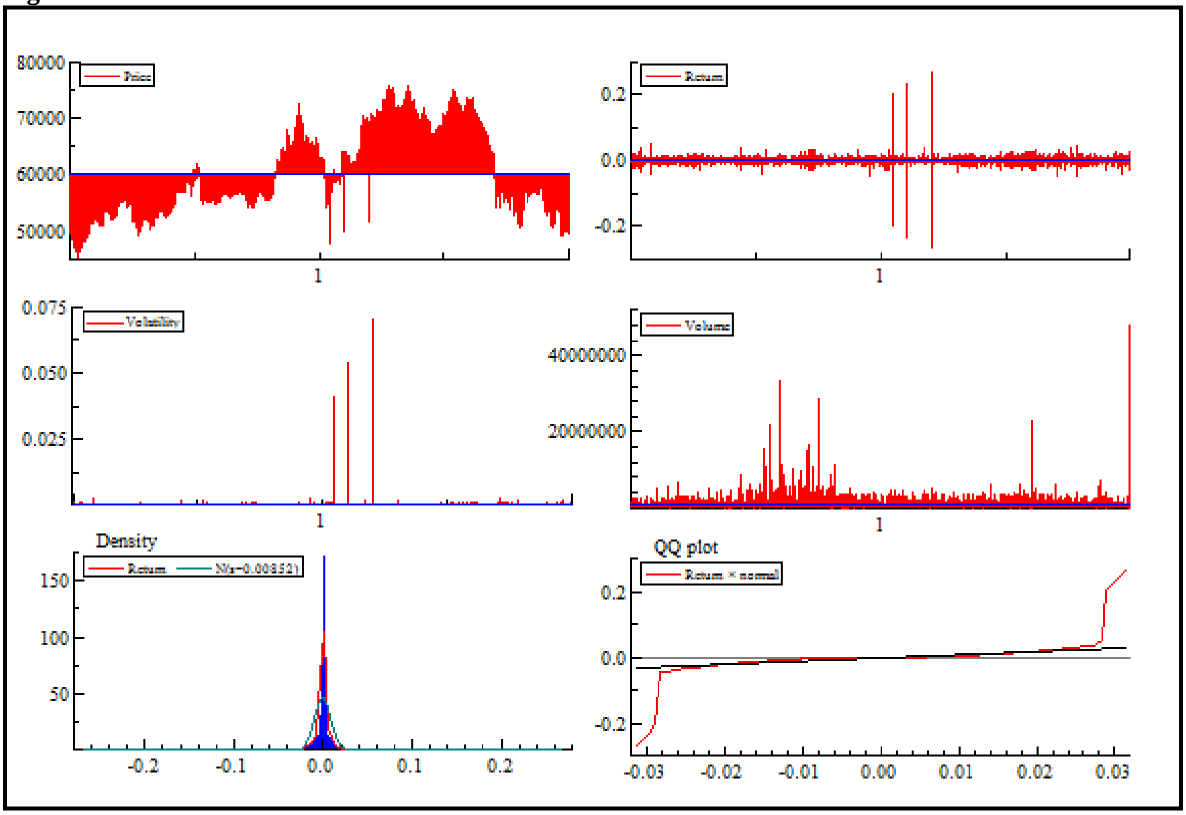
Note: *SD* indicates standard deviation.
JB denotes Jarque-Bera (1980) normality test statistic which is asymptotically distributed as Chi-square distribution with 2 degrees of freedom. As a benchmark, the 1% critical value equals 9.21.
$Q(50)$ and $Q_s(50)$ are the Ljung-Box Portmanteau test statistics with 50 degrees of freedom based on standardized and squared standardized residuals, respectively. *P*-values against the null hypothesis of white noise are reported in parenthesis.
$\ln vf_t$ is the detrended futures contract volume denoting the residuals of the equation:
$\ln vf_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t$ where $\ln vf_t$ denotes the logarithm of the trading volume of futures contracts.
*, ** denote statistical significance at 1% and 10% level.

5.2 Distributional Properties of ISE-30 Index Futures Series

Following the analysis of the characteristics of intraday data, the properties of the empirical distributions of the 15-minutes ISE-30 index futures return series are crucial in the proper selection of predictive models for volatility. Figure 4 presents the patterns of the price, return and volume series of ISE-30 index futures for the whole period. The price appears to be steadily increasing over the 308 trading days, while the corresponding 2,532,990 15-minutes returns are all seemingly scattered around zero. At the same time, the figure suggests that the volatility is not constant over time and tends to cluster, i.e. periods of high volatility can be clearly distinguished from low volatility periods.

Quantile-Quantile (QQ) plots can be used to observe departures from normality and thus give a nonparametric view to assess whether a distribution is skewed or heavy tailed. The QQ-plot is a scatter plot of empirical quantiles of a given distribution on the vertical axis against theoretical quantiles on the horizontal axis. This plot shows whether the plotted data is scattered around the 45-degree line (i.e. the data is normally distributed) or not. A density graph shows the relative frequency distribution of the time-series compared to, for example, the normal density of the same mean and standard deviation. The density graph in Figure 4 can be used to obtain a non-parametric view in order to assess whether the raw returns distribution is skewed or heavy tailed. This is done by plotting the individual against a normal distribution. The ISE-30 index futures return' density clearly has a higher peak than a normal distribution, implying that there is an excess kurtosis. The skewness is close to normal. A QQ-plot for ISE-30 index futures return is also shown in Figure 4 in order to visualize how far from normal the data set is. The density graph and QQ-plot against the normal distribution presents that ISE-30 index futures return distribution also exhibits fat tails confirming the results in Table 6.

Figure 4: ISE-30 Index Futures Series and Tail Distribution



Note: Top: Plots of intra-day prices (left), corresponding returns (right) for the ISE-30 index futures.
Middle: Plots of intra-day volatility (left) and trading volume (right) for the ISE-30 index futures.
Bottom: Density graph (left) and QQ-plot (right) for the ISE-30 index futures returns against a normal distribution.

Empirical evidence in financial markets displays a strong seasonality within the trading day. Early studies on intraday reported seasonality used data resampled at regular time intervals (e.g. hourly, every half hour, every 5 minutes etc.) and focused mainly on the behavior of the intraday volatility (e.g. Bollerslev and Domowitz, 1993; Andersen and Bollerslev, 1997a, 1998; Beltratti and Morana, 1999). In the context of irregularly time-spaced intraday data, Engle and Russell (1998) reported higher trading activity at the beginning and ending of the trading day, and slower trading activity in the middle of the day. Traders are very active at the opening as they engage in transactions to benefit from the overnight news. Similarly, at the closing, some traders prefer to close their positions before the end of the session. Lunchtime is naturally associated with reduced trading activity. To prevent the distortion of results, the intraday seasonality must be taken out prior to the estimation of any models.

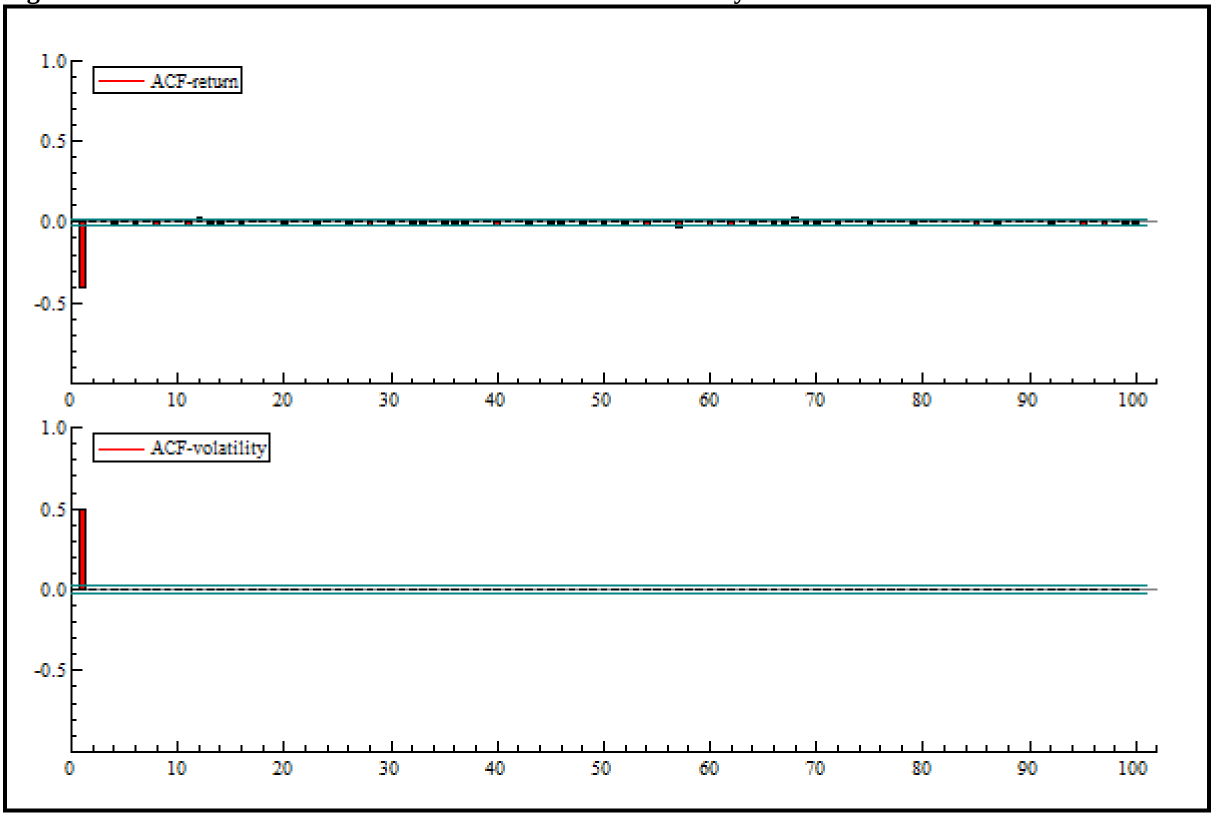
To investigate the intraday seasonality of returns and volatility and the reasons for lack of independence (see Table 6), the autocorrelation function of returns and volatility measured at 15-minute intervals for the first 100 lags is plotted against its lags with the 95% Bartlett confidence intervals in Figure 5. If series are distributed normally, these bands represent the 5% confidence interval for the hypotheses that the mean estimates are zero. As the distribution of returns is known to be leptokurtic, the displayed intervals are much tighter than expected, however.

Goodhart (1989) and Goodhart and Figliuoli (1991) first reported the existence of negative first-order autocorrelation of returns[37] at the highest frequencies, which disappears once the price formation process is over. As indicated in Figure 5, it is apparent that there is significant autocorrelation at the first lag. Still, the presence of serial dependence in return series at the first lag suggests that it may be appropriate to include autoregressive components in predictive models of return. For longer lags, the autocorrelations decays more rapidly and mainly lie within the 95% confidence interval of an identical and independent Gaussian distribution. Therefore, the data do not display any seasonal patterns. However, given Ljung-Box-Pierce Portmanteau test statistics for return and volatility in Table 6, it is obvious that taking into account

[37] The negative first-order autocorrelation of returns is consistent with the noisy rational expectation equilibrium (see e.g., Makarov and Rytchkov, 2007).

intraday seasonality has not removed the autocorrelation. These results are evidence that the 15-minute returns tend not to be independent and exhibit “volatility clustering”[38]. This suggests that the data display all the previously documented characteristics of the unconditional distribution of returns that are used to conform to the various GARCH specifications discussed in the following sections.

Figure 5: The Autocorrelation Function of Returns and Volatility



Not: The autocorrelation function for the ISE-30 index futures returns and volatility is plotted for different time lags in minutes up to 100 min. The two horizontal lines represent Bartlett’s formula for MA(q) 95% confidence interval of an i.i.d. Gaussian process.

As nonlinear dependence and heavy-tailed unconditional distributions are characteristic of conditionally heteroskedastic data, this behavior can be captured by

[38] In the presence of volatility clustering, the squared standardized residuals series should be highly autocorrelated. Indeed, as is well known, the dependence for the squared returns is very high on an intraday basis.

incorporating ARCH or GARCH structures in the model, allowing conditional heteroskedasticity by conditioning the volatility of the process on past information. As the GARCH model is capable of capturing these characteristics of this type of data, the relation between return variability and volume is also investigated by employing GARCH frameworks.

CHAPTER 6

EMPIRICAL RESULTS

The empirical results are presented as follows. First, the results from tests for stationarity applied to the entire sample are reported. These results provide the justification for the selected models. Next, in order to examine the intraday volatility, the evidence for the GARCH models based on different distributions are presented in accordance with the empirical features of the distribution of ISE-30 index futures returns reviewed in the previous section. Volatility estimates are required for efficient pricing of ISE-30 index futures as well as for the effective use of this instrument in managing and hedging risk. Finally, the success of each time-varying volatility models are assessed and compared.

6.1. Preliminary Analysis

As a preliminary procedure, the stochastic process is tested in the autoregressive representation of ISE-30 index futures series utilizing the most commonly used unit root tests, namely: Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and the KPSS (Kwiatoski *et al.,* 1992) tests. While both of these are used to test for the existence of a unit root in the residuals, they completely differ with regard to their hypotheses. The null hypothesis of the ADF test is that the series contains a unit root against the alternative hypothesis that the series is stationary, while the null hypothesis of the KPSS test is that the series is stationary. Both tests are used to determine the stationarity of each series and carried out with two different specifications, that is, with either a constant or a trend. The KPSS test complements the ADF test and concerns regarding the power of either test can be addressed by comparing the significance of statistics from both tests.

Table 7: Unit Root Test Results

	ADF		KPSS	
	No Trend	**With Trend**	**No Trend**	**With Trend**
		04.01.2007-21.03.2008		
Return (4 lag)	-51.7643*	-51.7958*	0.2092	0.0394
ln v_f (1 lag)	-65.5964*	-65.5890*	0.1704	0.1704
		04.01.2007-06.09.2007 (Pre-extension Period)		
Return (3 lag)	-46.3061*	-46.3095*	0.0196	0.0187
ln v_f (1 lag)	-48.1134*	-48.1192*	0.3469	0.3315*
		07.09.2007-21.03.2008 (Post-extension Period)		
Return (4 lag)	-34.0351*	-34.1018*	0.2193	0.0275
ln v_f (1 lag)	-44.7622*	-44.7535*	0.2864	0.2833*

Note: ADF: Optimum lag is selected according to the AIC, critical values are based on Davidson and MacKinnon (1993); critical values are -2.565 (99%), -1.940 (95%) and -3.961 (99%), -3.411 (95%) with no trend and with trend, respectively.
KPSS: Optimum lag is selected according to Schwert (1989); critical values are 0.739, 0.463, 0.347 for the model without trend; 0.216, 0.146, and 0.119 for the model with trend and for 1, 5, and 10% respectively (Kwiatkowski *et al.*, 1992).
* denotes rejection of null hypothesis at 1%.

Table 7 represents the results of the unit root tests for return and logarithm of the trading volume series. The ADF test rejects the null hypothesis of a unit root for all series at the 1% level of significance while the KPSS test cannot reject the null of stationarity for both return and detrended trading volume series without trend, indicating that all series are stationary. Hence, the whole series are suitable for the long memory tests. This observation suggests that the series of the ISE-30 index futures follow integrated of order one[39], I(1), processes.

Statistical analyses reported in the previous section point out that the 15-minute returns exhibit statistically significant autocorrelation at the first lag. It is necessary to remove the predictable component of returns so as to produce a return innovation, ε_t with a conditional mean of zero, before a GARCH model is specified for the variance. One possible way of producing an uncorrelated process from the 15-minute return series is to specify the level of returns in the following AR(q) process:

$$R_{i,t} = \mu + \sum_{j=1}^{q} \eta_j R_{i-j,t} + \varepsilon_{i,t} \tag{27}$$

$$\varepsilon_{i,t} \sim N(0, \sigma_{i,t}^2)$$

To determine the order q of an AR process, Akaike Information criterion (AIC)[40] is used. AR(2) model best fits the data and is preferred for the conditional mean equation by the criterion[41]. In order to determine whether ARCH specification is necessary or not, the residuals, ε_t, of the conditional mean equation for ARCH effects are examined. The squared residual series $\{\varepsilon_t^2\}$ is examined to check for heteroscedasticity by Lagrange multiplier test (LM test). To examine ARCH(q) effect, the model is specified as follows,

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[39] A series that can be made stationary by differencing is said to be integrated, or to possess a unit root.

[40] The AIC to be minimized is defined as follows,

$$AIC = -2 \log L(e) + 2\gamma$$

where γ denotes the number of estimated parameters, L(e) is the value of the Log-likelihood.

[41] As Miller *et al.*, (1994) put it, the AR(1) model is too simple and insufficient to get rid of all spurious autocorrelation embedded in stock indexes. Therefore, an attempt to at make correct for such autocorrelation would be worthwhile.

$$\varepsilon_{i,t}^2 = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{i-j,t}^2 \tag{28}$$

where ε is the error term from the AR(2) filtered series and q is the number of lags used in the model. This LM test checks the hypothesis that $\{\varepsilon_{i,t}\}$ is an iid white noise against the alternative that it is an ARCH(1) process. The lag-length (1) for ARCH-LM test is determined by AIC criterion. The results indicate that there exists very strong ARCH effect in the residual series of return for each period, as evidenced by the large and significant F-statistics and Engle's LM test statistics in Table 8. It rejects the null hypothesis of no ARCH effects at the 1% level of significance. The residual series, $\varepsilon_{i,t}$, are uncorrelated since second-order or higher-order autocorrelation is not detected in the 15-minute return series. Therefore, AR(2) model is extended to take into consideration these ARCH effects.

Table 8: ARCH-LM Test Results

Period	Constant	Squared residuals	F-statistics	LM-statistics
04.01.2007-21.03.2008	$4.29*10^{-5}$	0.265	672.6258	625.2366
	(0.0001)	(0.000)	(0.000)*	(0.000)*
04.01.2007-06.09.2007	$4.02*10^{-5}$	0.249	329.2018	308.7593
(Pre-extension Period)	(0.0031)	(0.000)	(0.000)*	(0.000)*
07.09.2007-21.03.2008	$4.64*10^{-5}$	0.282	338.2245	311.3990
(Post-extension Period)	(0.0011)	(0.000)	(0.000)*	(0.000)*

The numbers in the parentheses are *p*-values. * denotes rejection of null hypothesis at 1%.

6.2. GARCH Models

The existence of ARCH effects makes it appropriate to apply ARCH types of models to model the conditional variance error terms, ε_t. GARCH process of orders p and q, denoted as GARCH(p,q), for conditional variance of $\varepsilon_{i,t}$ at tick *i* on day *t*, used in this research can be specified as follows:

$$\sigma_{i,t}^2 = \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{i-k,t}^2 + \sum_{j=1}^{p} \beta_j \sigma_{i-j,t}^2 \tag{29}$$

under the constraints of $p \geq 0, q > 0, \alpha_0 > 0, \alpha_k \geq 0$ and $\beta_j \geq 0$ which are sufficient for stationarity. The coefficient of ARCH is typically interpreted as news (shock) coefficient that measures the impact of recent news on volatility. Similarly, the GARCH coefficient is known as the persistency coefficient and measures the impact of past volatility on the current volatility in a long memory.

In this section, ARCH specifications are estimated on the returns sampled at intraday frequencies. First, the system equations is estimated and the evidence of the GARCH(1,1) model based on different distributions are presented, and then an asymmetric effect by using an EGARCH(1,1) and TGARCH(1,1) models is introduced where the current conditional volatility estimate for an asset is often dependent on the size and sign of past observations.

The estimation of GARCH(1,1) specification is confined since it has been shown to be a parsimonious representation of conditional variance that adequately fits many high-frequency time series (see Bollerslev, 1987 and Engle, 1993). Moreover, since the autocorrelation for each of the series decay after one lag, AR(2)-GARCH(1,1) appears to be the appropriate model. AR(2)-GARCH (1,1) model can be specified as follows[42]:

$$
\begin{aligned}
R_{i,t} &= \mu + \sum_{j=1}^{2} \eta_j R_{i-j,t} + \varepsilon_{i,t} \\
\sigma_{i,t}^2 &= \alpha_0 + \alpha_1 \varepsilon_{i-1,t}^2 + \beta_1 \sigma_{i-1,t}^2
\end{aligned}
\qquad (30)
$$

The parameters are estimated jointly using numerical techniques to maximize the log-likelihood functions. The log-likelihood function is computed from the product of all conditional densities. The iteration is carried out until convergence to the optimum is obtained. An empirical regularity found almost universally across all assets is that high frequency returns are leptokurtic. Early evidence for this dates back to Mandelbrot (1963) and Fama (1965). Clark (1973) established that a stochastic process is thick tailed if it is conditionally normal with changing conditional variance. ARCH models have this property, but it is often found that these models do not adequately account for leptokurtosis. As a result, several other distributions have been employed to fully capture the degree of tail thicknesses[43]. The results of fitting pure GARCH models under the assumption of Gaussian distribution and Generalized Error distribution[44] (GED) to the 15-minute return series are represented in Table 9 through Table 14. All results are presented for each distribution and for each GARCH model whose specification is always order (1,1). In order to address the nature and structure of the volatility, the whole period is

[42] Different GARCH(p,q) models were initially fitted to the data and compared on the basis of the Akaike and Schwarz Information Criteria (AIC and SIC) from which a GARCH(1,1) model was deemed most appropriate for modeling the fifteen-minute return process for ISE-30 index futures.
[43] While the numerical maximization of the log-likelihood function failed to converge after 500 iterations, the GARCH models under one of the thick tailed distribution (Student-*t*) assumption are excluded from the results.
[44] When using GED distributions, the scale parameter ς is estimated as a part of the GARCH model. By employing GED fix parameter, the scale parameter ς is fixed for 1.5 at a certain value during the estimation.

divided into pre- and post extension period consistent with its extended trading hours from September 7, 2007, and AR(2)-GARCH(1,1) technique has been estimated separately for each subsample and whole sample.

Table 9 indicates the results of fitting restricted AR(2)-GARCH(1,1) process to the 15-minute ISE-30 index futures return series for the sample period.

Table 9: AR(2)-GARCH(1,1) Model Estimation

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
	GED	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**
			Mean Equation			
μ_0	$-2.77*10^{-8}$	$7.02*10^{-5}$	$3.78*10^{-6}$	$7.35*10^{-5}$	$-1.39*10^{-9}$	$6.91*10^{-5}$
	$(3.40*10^{-6})$	$(4.65*10^{-5})$	$(7.16*10^{-6})$	$(6.36*10^{-5})$	$(2.18*10^{-6})$	$(8.73*10^{-5})$
η_1	-0.05391*	-0.2299*	-0.0820*	-0.2770*	$-1.08*10^{-5}$	-0.1811*
	(0.0055)	(0.0140)	(0.0055)	(0.0191)	(0.0018)	(0.0211)
η_2	$3.06*10^{-5}$*	-0.0541*	-0.0079**	-0.0644*	$-2.26*10^{-7}$	-0.0500**
	(0.0021)	(0.0121)	(0.039)	(0.0170)	(0.0007)	(0.0201)
			Variance Equation			
α_0	$8.31*10^{-6}$	$1.00*10^{-5}$*	$1.08*10^{-5}$*	$7.73*10^{-6}$*	$9.22*10^{-6}$*	$1.17*10^{-5}$*
	$(4.67*10^{-7})$	$(2.50*10^{-7})$	$(8.51*10^{-7})$	$(3.74*10^{-7})$	$(7.67*10^{-7})$	$(3.58*10^{-7})$
α_1	0.6672*	0.2596*	0.8061*	0.2291*	0.6357*	0.2905*
	(0.0572)	(0.0141)	(0.1092)	(0.0207)	(0.0780)	(0.0215)
β_1	0.3177*	0.4354*	0.1929*	0.5117*	0.3376*	0.4004*
	(0.0222)	(0.0136)	(0.0357)	(0.0221)	(0.0306)	(0.0181)
ς	0.6378*	1.5*	0.5754*	1.5*	0.6648*	1.5*
	(0.0061)		(0.0085)		(0.0100)	
LL	36173.79	34039.75	20607	19279	15600.31	14772.57
AIC	-8.1742	-7.692	-8.3350	-7.796	-7.988	-7.564

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria.

[a] The scale parameter ς is exactly equal to 1.5.

*, ** indicate rejection at the 1% and 5% significances level.

The estimated coefficients for the conditional mean and variance equations based on the assumption that the error series follows generalized error distributions[45] are presented in Table 9. Consistent with most financial data, with a few exceptions, most of the parameter estimates of the AR(2)-GARCH(1,1) model with generalized error distributions (GED) for ISE-30 index futures are found to be highly statistically significant. Examination of the lagged ISE-30 index future return variables in the first and second period denotes that all of the variables have a negative sign and are statistically significant, indicating that a mean reversion process is present in the intraday data. Turning to the whole period, the testing results show that each variable has a negative sign and is statistically significant only under GED with fix parameter. The estimates of α_0 are all positive and considerably smaller than the sample variances shown in Table 9. This is due to changing conditional variance over time and their eventual contribution to unconditional variances.

In the estimation of volatility, the α_1 coefficient represents the weight applied to the news measured as the shock of the preceding 15 minutes interval, such that the larger the α_1 coefficient the more a market reacts to news. The β_1 coefficient represents the weight applied to the previous forecast of volatility. In numerous studies of developed countries, it is common to observe that the value of coefficient β is larger than that of coefficient α. In comparison to developed markets, emerging markets occasionally have a larger α coefficient and a smaller β coefficient. As shown in Table 9, the estimated α_1 coefficient in the conditional variance equation is considerably larger than β_1 coefficient. The implication is that the volatility is more sensitive to news in the market place than its lagged values which lead to a more

[45] In spite of numerous starting values are used, the restricted GARCH(1,1) model under Gaussian distribution does not converge. Therefore, it will not be possible to report the results.

"spiky" volatility. Therefore, this study indicates that the Turkish derivatives market reacts somewhat more to recent news which is consistent with Alexander (2001).

One important characteristic of stock returns is the tendency for volatility clustering such that large changes (small changes) in returns are often followed by other large changes (small changes). The implication of such volatility clustering is that volatility shocks today will influence the expectation of volatility in the future. To assess the degree of persistence in volatility implied by GARCH model, it is useful to consider the aggregation of α_1 and β_1 coefficients. If the degree of persistence is close to one, this implies that the current volatility of intraday returns is affected by the past volatility that tends to persist over time: the actual persistence of volatility must depend on the persistence of the exogenous variables. Further, a period of high volatility in stock returns will eventually give way to normal (lower) level of volatility and a lower period of volatility will be replaced with normal (higher) level of volatility. This process of reversion to a normal or mean level of volatility implies that even if volatility persistence exists, as long as the sum of the α_1 and β_1 coefficients is significantly less than one, the volatility process, while having a long memory, will still be mean reverting or stationary.

The persistence in volatility as measured by sum of α_1 and β_1 in GARCH(1,1) model under the assumption of generalized error distribution is closer to unity for ISE-30 index futures returns for each period. The fact that the aggregation of α_1 and β_1 are fairly close to one indicates the persistence of past volatility in affecting current volatility (see Engle and Bollerslev, 1986). Moreover, these results provide strong evidence that the 15-minute return series can be characterized by a GARCH(1,1) specification with GED. This implies that current volatility of intraday return can be explained by past volatility that tends to persist over time. For GED an extra parameter, ς, is estimated. The GED is leptokurtic when $\varsigma < 2$. This parameter, which is the scale parameter, is significant at any level. Based on the findings, the symmetric distributions with fatter tails clearly outperform the Gaussian. Owing to the well-known non-normality of the disturbance term and the details for the AIC and log-likelihood, the distribution is better approximated by GED than GED with a fixed parameter for the restricted version of GARCH(1,1) model.

The occurrence of time-dependent conditional heteroscedasticity could be due to the arrival of news and irregular information. Using the MDH framework, Lamoureux and Lastrapes (1990) argued that the observed GARCH effects in financial time series may be explained as a manifestation of time dependence in the rate of evolution of intraday equilibrium returns. Especially for high-frequency intraday data, the variables likely to be of most influence relate to trade information. Trade information leads to a change in expectations, which in turn leads to a change in prices. One means of proxying the arrival of this trade information is to introduce the trading volume into the conditional variance equation.

Table 10: AR(2)-GARCH(1,1) Model Estimation with Trading Volume

	Panel A: 04.01.2007-21.03.2008			**Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)**			**Panel C: 07.09.2007-21.03.2008 (Post-extension Period)**		
	Normal	**GED**	**GED fix parameter[a]**	**Normal**	**GED**	**GED fix parameter[a]**	**Normal**	**GED**	**GED fix parameter[a]**
μ_0	$-1.94*10^{-4}$	$-1.15*10^{-4}$	$1.29*10^{-5}$	$-1.17*10^{-4}$	$-4.35*10^{-4}$**	$3.60*10^{-5}$	$-1.30*10^{-5}$	$-9.82*10^{-5}$	$-9.27*10^{-5}$
	(0.0002)	(0.0002)	($4.66*10^{-5}$)	(0.0002)	(0.0002)	($5.93*10^{-5}$)	(0.0003)	(0.0003)	(0.0002)
η_1	-0.4807*	-0.4820*	-0.2688*	-0.5026*	-0.5027*	-0.2644*	-0.4601*	-0.4599*	-0.4592*
	(0.0288)	(0.0291)	(0.0137)	(0.0409)	(0.0407)	(0.0182)	(0.0422)	(0.0419)	(0.0313)
η_2	-0.1872*	-0.1869*	-0.0797*	-0.1872*	-0.1872*	-0.0570*	-0.1881*	-0.1881*	-0.1877*
	(0.0312)	(0.0314)	(0.0120)	(0.0436)	(0.0437)	(0.0154)	(0.0479)	(0.0475)	(0.0337)
α_0	$4.25*10^{-5}$*	$4.24*10^{-5}$*	$8.84*10^{-6}$*	$3.58*10^{-5}$*	$3.52*10^{-5}$*	$9.34*10^{-6}$*	$4.85*10^{-5}$*	$4.81*10^{-5}$*	$3.87*10^{-5}$*
	($1.10*10^{-6}$)	($1.61*10^{-6}$)	($3.64*10^{-8}$)	($3.36*10^{-6}$)	($3.24*10^{-6}$)	($3.97*10^{-7}$)	($5.01*10^{-6}$)	($5.49*10^{-6}$)	($4.38*10^{-6}$)
α_1	0.1451*	0.1491*	0.2595*	0.1508*	0.1512*	0.2457*	0.1480*	0.1475*	0.1472*
	(0.0166)	(0.0162)	(0.0108)	(0.0202)	(0.0206)	(0.0198)	(0.0242)	(0.0253)	(0.0284)
β_1	0.5962*	0.5979*	0.4864*	0.5983*	0.5973*	0.4211*	0.5928*	0.5906*	0.5869*
	(0.0124)	(0.0116)	(0.0041)	(0.0335)	(0.0347)	(0.0219)	(0.0436)	(0.0443)	(0.0480)
ψ	$-1.64*10^{-5}$*	$-1.64*10^{-5}$*	$-2.93*10^{-6}$*	$-1.38*10^{-5}$*	$-1.36*10^{-5}$*	$-2.83*10^{-6}$*	$-2.02*10^{-5}$*	$-1.99*10^{-5}$*	$-1.59*10^{-5}$*
	($3.06*10^{-7}$)	($4.00*10^{-7}$)	($1.12*10^{-8}$)	($5.38*10^{-7}$)	($5.32*10^{-7}$)	($6.23*10^{-8}$)	($2.58*10^{-7}$)	($6.83*10^{-7}$)	($2.98*10^{-7}$)
ς		1.9928*	1.5*		1.9885*	1.5*		1.9929*	1.5*
		(0.0095)			(0.0128)			(0.0153)	
LL	30304.30	30314.05	34234.89	17267.77	17303.29	19398.04	13143.23	13167.22	13896.48
AIC	-6.847	-6.849	-7.735	-6.984	-6.998	-7.845	-6.729	-6.741	-7.115

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. ψ represents for trading volume. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria.

[a] The scale parameter ς is exactly equal to 1.5.

*, ** indicate rejection at the 1% and 5% significances level

Table 10 reports the coefficient estimates for the AR(2)-GARCH(1,1) model when including the contemporaneous trading volume in the conditional variance equation of ISE-30 index futures returns. The persistence of the conditional heteroskedasticity of the return variability is reduced slightly after including the trading volume to the variance equation in the unrestricted version of GARCH(1,1) model with generalized error distributions. Also, when distribution is selected as a Gaussian distribution, the sum of α_1 and β_1 terms has the same value with GED. Therefore, trading volume has not been found to have a significant impact on the estimated coefficients of the model under each distribution when included in the specification of the conditional variance in comparison with the benchmark model. Volume, in other words, can act as a proxy for volatility measures. In most cases[46], the inclusion of trading volume as an explanatory variable in the conditional variance equation results in a substantial reduction of volatility persistence. For emerging markets, this evidence is weaker[47]. The results indicate that volatility persistence does not vanish under the presence of the volume series in the conditional variance equation; therefore MDH is not a relevant explanation in determining the GARCH effects in the Turkish derivatives market, which is relatively young, compared to other emerging markets.

Nevertheless, the volume parameter, ψ, as a proxy for information flow is found to be statistically significant at 1% level, but negatively related with volatility for each period and every distribution process in particular contrary to the MDH. The findings

[46] Lamoureux and Lastrapes (1990), Kim and Kon (1994), Andersen (1996), Gallo and Pacini (2000) in the US, Brailsford (1994) in Australian, Omran and McKenzie (2000) in the UK, Pyun *et al.* (2000) in Korea, Ciner (2003) in Turkey, Bohl and Henke (2003) in Poland, Gallagher and Kiely (2005) in Ireland.

[47] Huang and Yang (2001) in Taiwan, Bohl and Henke (2003) in Poland, Ahmed *et al.* (2005) in Malaysia, Wang *et al.* (2005) in China, Salman (2002), Yuksel (2002), Baklacı and Kasman (2006) in Turkey.

are moderately consistent with the Sequential Information Arrival Hypothesis[48] (SIAH) of Copeland (1976) and Jennings *et al.* (1981). All verify the existence of an inverse relationship between volatility and volume dynamics.

From a different perspective, some academicians such as Kyle (1985) and Admati and Pfleiderer (1988) supported the idea that high volume is accompanied by high volatility. Admati and Pfleiderer (1988) argued that volume patterns emerge because informed and uninformed traders choose to trade at the same time in order to minimize transactions costs and informed traders are only active during high volume trading periods. However, the cost of information acquisition will require that informed traders make a profit, in which case they will not fully exhaust the price signal, again indicating that price volatility should be low. Therefore, price volatility is high when volume decreases and should fall when volume rises. This contradicts both the conclusion reached by Admati and Pfleiderer (1988) and the assertions of empiricists drawing on their work.

Another important implication about negative volume-volatility relationship made by French and Roll (1986) implies that informed trading is not the additional source of exogenous volatility. Instead, it suggests that informed trading serves to reduce exogenous volatility by dispersing and mixing price reactions to news. Easley and O'Hara (1992) also presented no opposition theory to the negative volume-volatility prediction. Their main conclusion on the relationship between volume and price changes is that price change is equal to price innovations in the absence of informed trading and unusual volumes. However, unusual volume, whether motivated by

[48] Under SIAH new information is received by all traders but not simultaneously. As a consequence individuals react to new information at different times creating a sequential reaction. Sequential reaction to news arrival is deemed to affect the price and therefore variation in price changes is potentially predictable with information on trading volume.

information or not, will disturb price changes. They further indicated that price will move in the direction of whichever quote is hit. So, if an informed trader finds out that the next price innovation is downwards and initiates a sell order now, the current price will be driven down by his order flow. This will close the gap between the price now and that predicted at the end of the next trading period, reducing the price change, as predicted above. Similar findings were reached by Girard and Biswas (2007) who claimed that as compared to developed markets, emerging markets show a greater response to large information shocks. In addition, emerging markets also exhibit greater sensitivity to the trading volume. The negative relation between volume and volatility suggests that informed traders tend to lead the speculative trading activity and drive bid-ask spreads higher, further diminishing the liquidity of those markets.

From this result, it is evident that the rate of information arrival measured by the volume series can be a significant source of the conditional heteroskedasticity in index returns in the Turkish futures market. The negative trading volume impact on volatility can be attributed to the relative inefficiency in these emerging markets.

To address the question whether the normal distribution presents an adequate representation of the stochastic behavior of the Turkish intraday return series, the estimated results of the scale parameter, ς, are also examined. The estimated values of the scale parameter that determine the thickness of the tails is $\varsigma > 1$ in each model specifications. These estimated values are statistically different from 2 at the 1% level of significance, indicating the GED provides a better representation of the stochastic behavior of the Turkish intraday futures return series than the normal distribution. Moreover, the reported AIC and log likelihood envisage with low and high value statistics respectively highlighting the fact that GARCH(1,1) models with GED more accurately estimate the series than Gaussian distribution.

One of the main drawbacks of the GARCH specification is the assumption that both positive and negative shocks have the same impact on future volatility. In this perspective, in order to build more realistic models which can take into account the different impact of news, asymmetric models were introduced. These models can measure the different impact of good and bad news on future volatility. As previously detected in the unrestricted version of GARCH(1,1) model, asymmetric distributions might lead to this outcome, which is investigated via EGARCH and TGARCH modelings.

The EGARCH model allows for asymmetric volatility impact of past standardized innovations, a feature often attributed to the behavior of stock market prices. To analyze the effect of trading volume on return volatilities, the dynamic properties of the volatilities are modeled by excluding the trading volume. The AR(2)-EGARCH(1,1) model results with asymmetric effect for each distribution models are represented in Table 11.

Table 11: AR(2)-EGARCH(1,1) Model Estimation

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
	GED	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**
μ_0	$-9.66*10^{-9}$	$2.08*10^{-4}$*	$-1.66*10^{-7}$	$1.40*10^{-4}$**	$-6.43*10^{-9}$	$3.14*10^{-4}$*
	($6.44*10^{-7}$)	($4.75*10^{-5}$)	($3.50*10^{-6}$)	($6.75*10^{-5}$)	($3.60*10^{-6}$)	($8.80*10^{-5}$)
η_1	$-2.02*10^{-6}$	-0.2114*	-0.0281*	-0.2411*	$-1.55*10^{-5}$	-0.1820*
	(0.0007)	(0.0128)	(0.0046)	(0.0169)	(0.0022)	(0.0211)
η_2	$-2.26*10^{-5}$	-0.0470*	-0.0001	-0.4448*	$1.20*10^{-5}$	-0.0585*
	(0.0003)	(0.0113)	(0.0018)	(0.0166)	(0.0016)	(0.0152)
α_0	-4.1760*	-3.676*	-5.9937*	-2.6844*	-3.9194*	-5.2307*
	(0.2385)	(0.1107)	(0.4332)	(0.1569)	(0.2811)	(0.1979)
β_1	0.6353*	0.6735*	0.4697*	0.7662*	0.6586*	0.5273*
	(0.0221)	(0.0129)	(0.0402)	(0.0141)	(0.0261)	(0.0183)
ϕ_1	0.2893*	0.1084*	0.3715*	0.1113*	0.2338*	0.0789*
	(0.0236)	(0.0083)	(0.0381)	(0.0111)	(0.0307)	(0.0187)
ϕ_2	0.5645*	0.3863*	0.6404*	0.3127*	0.5722*	0.5138*
	(0.0266)	(0.0101)	(0.0421)	(0.0176)	(0.0339)	(0.0217)
ς	0.6050*	1.5*	0.5689*	1.5*	0.6732*	1.5*
	(0.0066)		(0.0085)		(0.0095)	
LL	36295.07	34065.98	20732.55	19343.90	15592.18	14751.12
AIC	-8.201	-7.697	-8.385	-7.824	-7.983	-7.553

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria.

[a] The scale parameter ς is exactly equal to 1.5.

*, ** indicate rejection at the 1% and 5% significances level.

For the sake of consistency, the lag length (p) chosen for the AR process in the mean equation (i.e. Eq. 27) is the same lag length previously used in the GARCH estimation. The autoregressive coefficients η_1 and η_2 in the conditional mean equations of model with fixed parameter of GED specifications analyzed in this study are mostly statistically significant at the 1% level, strongly indicating that the intraday percentage changes in the futures returns can be predicted using past intraday returns in the Turkish derivatives market[49].

The estimate of β_1 evaluates the persistence of shocks. For each distribution models, β_1 values are positive and highly significant at the 1% level for each period thereby implying that volatility is stationary, but mostly persistent. The magnitude of the coefficient reveals that the degree of persistence is low, ranging from 0.4697 to 0.7662, in case of ISE-30 index future, as seen in Table 11. For shock persistence to exist, the coefficient on β_1 should be close to one. The leverage effect terms ϕ_1 and ϕ_2 in EGARCH model are statistically significant. The coefficient ϕ_1 allows for the asymmetric response to positive and negative price changes (bad news and good news) in the conditional variance. A negative value of ϕ_1 means that a negative return shock or surprise tend to increase volatility more than a positive one of the same magnitude in the immediate future. However, one of the most striking results emerging from the estimations is that while testing the leverage effect, the coefficient of the asymmetric term, ϕ_1, is positive in all the periods, implying that the existence

[49] An AR specification in mean equation should adequately capture all serial correlation to make sure that all residuals are white noise. According to the results, the AR coefficients in the model are small, indicating that the serial dependence of the series is weak.

of leverage effect[50] is not observed in returns of the ISE-30 index futures. Therefore, the EGARCH models results do no reveal any asymmetric volatility effects in ISE-30 index futures under each GED specifications in each period.

To further examine whether trading volume can help to predict the future dynamics of the volatility, AR(2)-EGARCH(1,1) model is employed by including the trading volume factor.

[50] The asymmetric response is consistent with the leverage effect in which good news increases ISE-30 index futures prices, so decreasing leverage. This leads to lower volatility and a lower required rate of return.

Table 12: AR(2)-EGARCH(1,1) Model Estimation with Trading Volume

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
	GED	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**
μ_0	$4.11*10^{-8}$	$1.63*10^{-4}$*	$1.23*10^{-9}$	$1.28*10^{-4}$**	$1.35*10^{-8}$	$2.37*10^{-4}$*
	($3.33*10^{-7}$)	($4.54*10^{-5}$)	($1.93*10^{-7}$)	($6.04*10^{-5}$)	($2.96*10^{-6}$)	($7.94*10^{-5}$)
η_1	-0.0438*	-0.2032*	$-6.38*10^{-7}$	-0.2191*	$-1.17*10^{-6}$	-0.1808*
	(0.0003)	(0.0117)	(0.0001)	(0.0145)	(0.0022)	(0.0198)
η_2	$2.60*10^{-5}$	-0.0497*	$-1.51*10^{-6}$	-0.0453*	$3.62*10^{-6}$	-0.0596*
	(0.0002)	(0.0090)	(0.0002)	(0.0139)	(0.0012)	(0.0132)
α_0	-4.0073*	-4.9310*	-5.821*	-3.0571*	-4.3952*	-5.7853*
	(0.2401)	(0.0732)	(0.4189)	(0.1017)	(0.2987)	(0.2184)
β_1	0.6544*	0.5626*	0.4861*	0.7362*	0.6155*	0.4799*
	(0.0222)	(0.0066)	(0.0388)	(0.0092)	(0.0277)	(0.0203)
ϕ_1	0.2646*	0.1222*	0.3608*	0.1298*	0.2169*	0.0945*
	(0.0238)	(0.0112)	(0.0379)	(0.0110)	(0.0235)	(0.0204)
ϕ_2	0.5528*	0.4724*	0.6581*	0.3576*	0.6204*	0.5591*
	(0.0272)	(0.0138)	(0.0432)	(0.0153)	(0.0363)	(0.0241)
ψ	-0.1071*	-0.2725*	-0.1359*	-0.2279*	-0.1169*	-0.2671*
	(0.0175)	(0.0041)	(0.0259)	(0.0052)	(0.0257)	(0.0076)
ς	0.6465*	1.5*	0.5984*	1.5*	0.6711*	1.5*
	(0.0074)		(0.0098)		(0.0107)	
LL	36228.30	34323.50	20663.71	19504.27	15606.81	14852.36
AIC	-8.186	-7.756	-8.357	-7.888	-7.989	-7.604

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. ψ represents for trading volume. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria.

[a] The scale parameter ς is exactly equal to 1.5.

*, ** indicate rejection at the 1% and 5% significances level.

The results of the tests conducted to examine the ability of detrended trading volume to predict the future dynamics of return volatilities in the conditional variance specifications are reported in Table 12 using the AR(2)-EGARCH(1,1) model. The coefficient β_1 which measures the degree of persistency is positive and significant at 1%. As expected, β_1 slightly decreases once the traded volume is included in the EGARCH specification for the conditional variance. This shows that the trading volume has a relatively small impact on the coefficients of the volatility. Therefore, trading volume seems to affect the conditional volatility of the price formation, although at a slow rate. The variable of interest is ψ and this coefficient of detrended trading volume is negative and significant at 1% for each period and distributions. Therefore, trading volume possesses some information which is useful in predicting the future dynamics of return volatility. Accordingly, in thinly traded and highly volatile emerging markets, infrequent trading can cause prices to deviate substantially from fundamentals. An increase in the number of traders and speculative trading activity will realign prices with fundamentals, leading to more efficient prices and lower volatility.

The estimates of the parameter ϕ_1 are significant at 1% but positive in all periods under each GED specifications. The leverage effect is accounted if the coefficient ϕ_1 is less than zero, where a negative return shock or surprise seem to increase volatility more than a positive shock or surprise. Contrary to the expectations, there seem to be no leverage effects on the ISE-30 index futures contracts with the inclusion of trading volume variable to the variance equation as the coefficient is statistically positive. As such, bad news regarding ISE-30 index futures contract cause a smaller increase in volatility than good news of the same magnitude.

The final step is to investigate the volatility of the ISE-30 index futures with TGARCH model. By following the same procedure under GED specifications, the following results for AR(2)-TGARCH(1,1) are reported in Table 13[51].

[51] The TGARCH(1,1) model under Gaussian distribution does not converge after 500 iterations. Therefore, it will not be possible to report the results.

Table 13: AR(2)-TGARCH(1,1) Model Estimation

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
	GED	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**	**GED**	**GED fix parameter[a]**
μ_0	$4.50*10^{-8}$	$1.22*10^{-4}$**	$1.95*10^{-7}$	$1.09*10^{-4}$	$7.25*10^{-9}$	$1.31*10^{-4}$
	($1.19*10^{-6}$)	($5.68*10^{-5}$)	($4.12*10^{-6}$)	($7.32*10^{-5}$)	($2.87*10^{-6}$)	($9.23*10^{-5}$)
η_1	$-3.19*10^{-5}$	-0.1920*	-0.0372*	-0.2193*	$-2.81*10^{-6}$	-0.1537*
	(0.0019)	(0.0141)	(0.0061)	(0.0188)	(0.0028)	(0.0215)
η_2	$1.43*10^{-5}$	-0.0449*	$-9.49*10^{-5}$	-0.0478*	$-5.66*10^{-7}$	-0.0427**
	(0.0011)	(0.0117)	(0.0020)	(0.0164)	(0.0008)	(0.0192)
α_0	$9.83*10^{-5}$	$1.05*10^{-5}$*	$1.08*10^{-5}$*	$9.43*10^{-6}$*	$9.03*10^{-6}$*	$1.20*10^{-5}$*
	($5.17*10^{-7}$)	($2.54*10^{-7}$)	($6.96*10^{-7}$)	($4.64*10^{-7}$)	($7.41*10^{-7}$)	($3.60*10^{-7}$)
α_1	1.2339*	0.3956*	1.1613*	0.3749*	0.8754*	0.4166*
	(0.1599)	(0.0268)	(0.2527)	(0.0259)	(0.1307)	(0.0394)
β_1	0.267*	0.4126*	1.6433*	0.4394*	0.3482*	0.3848*
	(0.0212)	(0.0136)	(0.0295)	(0.0422)	(0.0313)	(0.0180)
θ_1	-0.926*	-0.2484*	-1.4142*	-0.2839*	-0.5450*	-0.2207*
	(0.1616)	(0.0268)	(0.2519)	(0.0423)	(0.1386)	(0.0440)
ς	0.613*	1.5*	0.5686*	1.5*	0.6773*	1.5*
	(0.0061)		(0.0082)		(0.0098)	
LL	36308.08	34068.94	20727.85	19297.06	15612.67	14782.09
AIC	-8.204	-7.698	-8.384	-7.805	-7.994	-7.569

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria.

[a] The scale parameter ς is exactly equal to 1.5.

*, ** indicate rejection at the 1% and 5% significances level.

The persistence of volatility, measured by β_1, is generally quite low for each period and indicates stationary persistence. It is apparent that volatility persistence is higher when GED with fixed parameter is used for the TGARCH model. It seems that the asymmetric model tends to possess better forecasting ability with a fatter tail distribution, indicating the superiority of the GED in describing the data series. TGARCH model implies that positive news at *i* interval has an impact of α_1 on the volatility at $i+1$, while negative news has impact of $(\alpha_1 + \theta_1)$. The presence of a leverage effect would imply that the coefficient θ_1 is positive that negative news has a larger effect on volatility than positive one. However, the θ_1 estimates that are used to capture the asymmetry are all negative and significant under GED with fix parameter. From the variance equation, it can be seen that when return decreases, the impact of $\varepsilon^2_{i-1,t}$ on $\sigma^2_{i,t}$, measured by $(\alpha_1 + \theta_1)$, is positive. On the other hand, when the return increases, the impact should only be α_1, which is greater than $(\alpha_1 + \theta_1)$ in this model, indicating the absence of a leverage effect.

The estimated coefficients of the AR(2)-TGARCH(1,1) model defined previously with the inclusion of detrended trading volume added as an additional explanatory variable in the conditional variance equation are reported in Table 14.

Table 14: AR(2)-TGARCH(1,1) Model Estimation with Trading Volume

	Panel A: 04.01.2007-21.03.2008			Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)			Panel C: 07.09.2007-21.03.2008 (Post-extension Period)		
	Normal	**GED**	**GED fix parameter[a]**	**Normal**	**GED**	**GED fix parameter[a]**	**Normal**	**GED**	**GED fix parameter[a]**
μ_0	0.0002	$-4.91*10^{-4}$**	$-1.28*10^{-4}$	$-1.74*10^{-4}$	$-5.29*10^{-4}$**	$-4.40*10^{-4}$*	$-1.58*10^{-4}$	$-1.63*10^{-4}$	$-1.34*10^{-4}$
	(0.0002)	(0.0002)	(0.0001)	(0.0003)	(0.0002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)
η_1	-0.4804*	-0.4821*	-0.4812*	-0.5026*	-0.5028*	-0.4953*	-0.4597*	-0.4598*	-0.4704*
	(0.0324)	(0.0318)	(0.0223)	(0.0432)	(0.0427)	(0.0234)	(0.0443)	(0.0445)	(0.0325)
η_2	-0.1872*	-0.1869*	-0.1864*	-0.1874*	-0.1873*	-0.1831*	-0.1881*	-0.1881*	-0.1876*
	(0.0361)	(0.0349)	(0.0237)	(0.0467)	(0.0458)	(0.0238)	(0.0496)	(0.0497)	(0.0349)
α_0	$4.66*10^{-5}$*	$4.31*10^{-5}$*	$3.31*10^{-5}$*	$3.60*10^{-5}$*	$3.53*10^{-5}$*	$1.64*10^{-5}$*	$4.81*10^{-5}$*	$4.82*10^{-5}$*	$3.89*10^{-5}$*
	$(9.24*10^{-7})$	$(1.46*10^{-6})$	$(1.08*10^{-6})$	$(3.38*10^{-6})$	$(3.31*10^{-6})$	$(1.39*10^{-6})$	$(4.94*10^{-6})$	$(5.46*10^{-6})$	$(4.33*10^{-6})$
α_1	0.1441*	0.1491*	0.1475*	0.1514*	0.1519*	0.1430*	0.1467*	0.1468*	0.1465*
	(0.0225)	(0.0195)	(0.0281)	(0.0235)	(0.0211)	(0.0153)	(0.0509)	(0.0539)	0.0534
β_1	0.5954*	0.5985*	0.5886*	0.5981*	0.5971*	0.5849*	0.5883*	0.5889*	0.5844*
	(0.0382)	(0.0112)	(0.0139)	(0.0333)	(0.0359)	(0.0298)	(0.0438)	(0.0443)	(0.0476)
θ_1	0.0457	0.0491	0.0488	0.0485	0.0491	0.0451	0.0486	0.0487	0.0484
	(0.0071)	(0.0366)	(0.0428)	(0.0659)	(0.0739)	(0.0406)	(0.0636)	(0.0649)	(0.0701)
ψ	$-1.79*10^{-5}$*	$-1.66*10^{-5}$*	$-1.26*10^{-6}$*	$-1.39*10^{-5}$*	$-1.36*10^{-6}$*	$-1.64*10^{-6}$*	$-1.98*10^{-5}$*	$-1.99*10^{-5}$*	$-1.59*10^{-5}$*
	$(8.55*10^{-8})$	$(3.03*10^{-7})$	$(2.21*10^{-7})$	$(5.05*10^{-7})$	$(5.54*10^{-7})$	(0.0000)	$(2.49*10^{-7})$	$(7.09*10^{-7})$	$(2.96*10^{-7})$
ς		1.991*	1.5*		1.985*	1.5*		1.991*	1.5*
		(0.0085)			(0.0133)			(0.0157)	
LL	30030.85	30235.86	32128.23	17241.01	17285.52	18887.55	13153.57	13153.76	13888.17
AIC	-6.785	-6.832	-7.259	-6.972	-6.990	-7.638	-6.734	-6.736	-7.110

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. ς is the scale parameter. ψ represents for trading volume. LL is the value of Log-likelihood function, and AIC is the Akaike information criteria. [a] The scale parameter ς is exactly equal to 1.5. *, ** indicate rejection at the 1% and 5% significances level.

The coefficient β_1, which measures the volatility persistence, is quite high under AR(2)-TGARCH(1,1) model with Gaussian distribution and GED as compared to the model without trading volume. Therefore, including trading volume in the conditional variance equation does not result in a reduction of volatility persistence for ISE-30 index future contract. The coefficient of detrended trading volume, ψ, is negative and significant at 1% for each period and distribution which is similar with the previous GARCH and EGARCH models' findings. The prevailing negative relationship between trading volume and volatility during each period reinforces the prior findings – variance decreases with an increase in trades and prices are adjusted through speculative trading. Indeed, in emerging markets, transactions are made through a broker. Brokers gather and process information from market sources regarding transactions that have taken place in that market, and then this information is then passed on to a trader (buyer or seller). As trading volume in the market increases, one would expect more information to be available in the market which, in turn, would improve market transparency and reduce uncertainty and market volatility. Asymmetry, measured by θ_1, is positive, as expected, but not significant in all periods indicating no leverage effect.

Preliminary evidence presented as previously points out that the intraday Turkish futures returns violate the assumption of normality and exhibit excess kurtosis beyond that permitted by the normal distribution, i.e., they are leptokurtic. In this study, GED uniformly provides better results, given the results of the preliminary evidence concerning the distributional properties of the intraday Turkish data. Moreover, the minimum Akaika Information Criteria (AIC) and maximum log-likelihood values as model selection criteria demonstrate the fact that EGARCH models better estimate the series than the traditional GARCH. However, the findings indicate that there is no asymmetry in the ISE-30 index futures. Therefore, the absence of leverage or asymmetric effects indicates that GARCH(1,1) model performs better than most rivals in terms of forecasting volatility of the ISE-30 index futures.

In general, the results of conditional volatility models used in this research, GARCH, EGARCH and TGARCH models do not support the MDH. Since the signs of trading volume parameter are estimated to be significantly negative and the volatility persistency cannot be eliminated when including trading volume into the processes under each distribution specifications, the MDH is not the appropriate proposition to explain the GARCH effects on ISE-30 index futures volatility. However, the existence of a negative relationship between trading volume and volatility is better explained by the Sequential Information Arrival Hypothesis of Copeland (1976) and Jennings *et al.* (1981). This can be partially attributed to an inefficient infrastructure in the market. Indeed, it is more likely that in the Turkish derivatives market, dissemination of information is asymmetric such that initially only well informed traders take positions. As information is sequentially transmitted from trader to trader, less informed traders also take positions. An increase in the number of traders and speculative trading activity will realign prices with fundamentals, leading to more efficient prices and lower volatility. As a result, it may be expected to observe that, in emerging markets, variance would decrease with an increase in trades and prices adjusted through speculative tradings.

6.3. Diagnostic Tests

A best-fitted GARCH model should capture all dynamic aspects of the conditional mean and variance. The estimated residuals should be serially uncorrelated and should not display any remaining conditional volatility. To test the adequacy of the mean and variance models, Ljung–Box Portmanteau test statistics can be performed. Insignificant test statistics indicate that the autocorrelation in the residuals and squared residuals has successfully been removed. Moreover, Engle's ARCH-LM test is used to see whether or not the conditional heteroskedasticity that existed in the return time series has been successfully removed. To assess validity of the estimated models, all the test results for ISE-30 index futures contract are represented in Table 15.a, 15.b and 15.c.

Table 15.a: Diagnostic Test Results

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
AR(1)-GARCH(1,1)						
	GED	**GED fix parameter**	**GED**	**GED fix parameter**	**GED**	**GED fix parameter**
$Q(50)$	58.647	46.339	42.712	34.947	36.077	31.516
	(0.188)	(0.621)	(0.758)	(0.948)	(0.930)	(0.981)
$Q_s(50)$	0.1543	0.1893	0.2076	0.1976	0.0635	0.0845
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
ARCH(1)	0.0024	$8.58*10^{-5}$	0.0035	0.0002	0.0004	$8.93*10^{-7}$
	(0.9613)	(0.9926)	(0.9530)	(0.9889)	(0.9837)	(0.992)
AR(1)-GARCH(1,1) with VOLUME						
$Q(50)$	112.94	47.812	76.920	41.988	61.413	60.294
	(0.000)*	(0.562)	(0.009)*	(0.783)	(0.129)	(0.151)
$Q_s(50)$	0.4413	0.2546	0.5274	0.3363	0.2383	0.2083
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
ARCH(1)	0.1803	0.0001	0.0768	0.0003	0.0909	0.0556
	(0.6707)	(0.9913)	(0.7818)	(0.9859)	(0.7631)	(0.8136)

Note: $Q(50)$ and $Q_s(50)$ are the Ljung-Box statistics with 50 degrees of freedom based on standardized and squared standardized residuals, respectively.
The ARCH(1) denotes the ARCH-LM test statistic with lag 1.
* indicates rejection at the 1% significance level.

Table 15.b: Diagnostic Test Results

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
	AR(1)-EGARCH(1,1)					
	GED	**GED fix parameter**	**GED**	**GED fix parameter**	**GED**	**GED fix parameter**
$Q(50)$	66.359	42.551	53.073	34.739	35.196	33.223
	(0.061)***	(0.764)	(0.357)	(0.950)	(0.944)	(0.967)
$Q_s(50)$	0.1121	0.1358	0.1831	0.1790	0.0612	0.0761
	(1.000)	(1.000)	(1.000)	(1.000)	(1.0000)	(1.000)
ARCH(1)	0.0050	0.0050	0.0061	0.0042	0.0015	0.0019
	(0.9434)	(0.9432)	(0.9376)	(0.9485)	(0.9695)	(0.9650)
	AR(1)-EGARCH(1,1) with VOLUME					
$Q(50)$	66.492	61.320	52.543	53.992	43.682	45.471
	(0.059)***	(0.131)	(0.376)	(0.324)	(0.723)	(0.655)
$Q_s(50)$	0.1612	0.2659	0.2694	0.6113	0.0784	0.1268
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
ARCH(1)	0.0065	0.0134	0.0109	0.0144	0.0020	0.0044
	(0.9359)	(0.9077)	(0.9166)	(0.9044)	(0.9640)	(0.9473)

Note: $Q(50)$ and $Q_s(50)$ are the Ljung-Box statistics with 50 degrees of freedom based on standardized and squared standardized residuals, respectively.
The ARCH(1) denotes the ARCH-LM test statistic with lag 1.
* indicates rejection at the 1% significance level.

Table 15.c: Diagnostic Test Results

	Panel A: 04.01.2007-21.03.2008		Panel B: 04.01.2007-06.09.2007 (Pre-extension Period)		Panel C: 07.09.2007-21.03.2008 (Post-extension Period)	
AR(1)-TGARCH(1,1)						
	GED	**GED fix parameter**	**GED**	**GED fix parameter**	**GED**	**GED fix parameter**
$Q(50)$	72.109	53.807	60.250	45.316	34.755	32.724
	(0.022)**	(0.331)	(0.152)	(0.662)	(0.950)	(0.972)
$Q_s(50)$	0.1439	0.1854	0.1666	0.2109	0.0632	0.0826
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
ARCH(1)	$1.43*10^{-5}$	0.0031	0.0002	0.0104	$8.17*10^{-6}$	0.0005
	(0.9970)	(0.9558)	(0.9877)	(0.9185)	(0.9977)	(0.9818)
AR(1)-TGARCH(1,1) with VOLUME						
$Q(50)$	112.78	109.79	76.420	69.350	60.525	59.176
	(0.000)*	(0.000)*	(0.009)*	(0.004)*	(0.146)	(0.176)
$Q_s(50)$	0.3823	0.3218	0.4906	0.3744	0.2041	0.1885
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
ARCH(1)	0.1006	0.0497	0.0392	0.0025	0.0504	0.0297
	(0.7511)	(0.8235)	(0.8431)	(0.9602)	(0.8223)	(0.8631)

Note: $Q(50)$ and $Q_s(50)$ are the Ljung-Box statistics with 50 degrees of freedom based on standardized and squared standardized residuals, respectively.
The ARCH(1) denotes the ARCH-LM test statistic with lag 1.
* indicates rejection at the 1% significance level.

The results of diagnostic tests show that GARCH models are well specified. Indeed, for each period and each model, Ljung-Box Portmanteau test statistics up to 50 lags for the squared standardized residuals are found insignificant indicating that the conditional variance equations are correctly specified. In each case, there is no evidence of additional autocorrelation in the squared standardized residuals, indicating that the chosen model specification provides an adequate fit. Also, when the variance equation is correctly specified, there should be no ARCH effect left in the standardized residuals. ARCH-LM statistics estimated for the presence of autocorrelation in the standardized residuals cannot reject the null hypothesis of no autocorrelation at the conventional levels. Therefore, the test results indicate that the conditional heteroskedasticity has been successfully removed that existed when the test was performed on the pure return series. Consequently, all the GARCH models adequately capture the persistence in volatility and there is no ARCH effect left in the residuals from the models.

CHAPTER 7

INTRADAY TRADING BEHAVIOR

Intraday market behavior is an area of interest examined under market microstructure literature. It is vital for market participants and academics and requires an extensive and rigorous examination. The availability of tick-by-tick transaction level data enables researchers to investigate intraday trading patterns. In order to find more detailed characteristics of price and volume series, the patterns of intraday returns, volatility and trading volume are investigated in addition to the previous empirical evidence.

This section reveals the empirical characteristics of the intraday pattern in the ISE-30 index futures series in 15-minute intervals. The intraday patterns of ISE-30 index futures are captured by dividing the trading day into 25 and 26 15-minute intervals before and after September 7, 2007, respectively. 15-minute measurement intervals are chosen since this period is considered to be long enough to capture the microstructure effects, and has been used in previous research (Chang *et al.,* 1995; Abhyankar *et al.,* 1997). By moving towards higher frequency in trading data, the results become more informative. It is well known that trading activity is not constant across the trading day. High-frequency traders need short-term or intraday price volatility and volume information on financial assets to make a profit in a trading day. In major markets, heavy trading activity is recorded in the earlier and later trading hours rather than around the midday (Andersen and Bollerslev, 1997a, 1997b; Wood *et al.*, 1985). The pattern of 15-minute intraday return, volatility and volume averages of the ISE-30 index futures across the 308 trading days are plotted in Figure 6 to examine how the trading friction changes across the trading day.

The intraday returns display a similar pattern both in pre- and post-extension periods and appear to show a smooth pattern at the opening and end of the morning session. However, high returns are observed between 10:45 a.m.-11:00 a.m. and 11:15 a.m.-11:30 a.m. in the morning session. A similar tendency for a smooth pattern at the opening of the afternoon session is broken with a slight fall between 14:45 p.m. and 15:00 p.m., but rises again during the 15:00-15:15 p.m. period. During the trading day, the highest and lowest return is experienced towards the end of the afternoon session. While the lowest return, about -0.10% is observed between 16:00 p.m. and 16:15 p.m., at the time of the opening of the US markets, the highest return, around 0.14%, occurs in the Turkish derivatives market between 16:15 p.m. and 16:30 p.m.

In the empirical studies regarding market microstructure, the focus is mainly on the deterministic pattern of intraday volatility, which is computed as squared returns. The high volatility at the beginning of the day is followed by a high spike in the middle of the morning session from 10:15 a.m. to 11:00 a.m. The opening interval of the afternoon trading session of TurkDEX, however, does not display the high volatility of the opening interval of the morning session. This indicates that traders are very active at the opening as they engage in transactions to benefit from the information asymmetry related to the overnight non-trading period, the primary driving force for widening volatility at the opening session. When the market opens, this information advantage reflects on prices, causing a larger volatility during the opening compared to off-trading period. There is a smooth pattern in the middle of the day. During the 14:45 to 15:15 p.m. time slot, volatility increases and peaks around 16:30 p.m. towards the end of the trading day. Increases in volatility are also apparent between the hours of 16:00 p.m. and 16:30 p.m., when trading takes place simultaneously in the European and US markets[52]. Excluding the last 30 minutes of trading, the volatility follows a U-shaped pattern with two peaks during the afternoon session. After the Turkish stock market closes, Turkish derivatives market remains open for additional 10 minutes. The sharp decrease in volatility at the end of the day occurs when the stock market is closed. The opening prices are more volatile than the closing prices, which supports the trading halt hypothesis formulated by Huang *et al.* (2000).

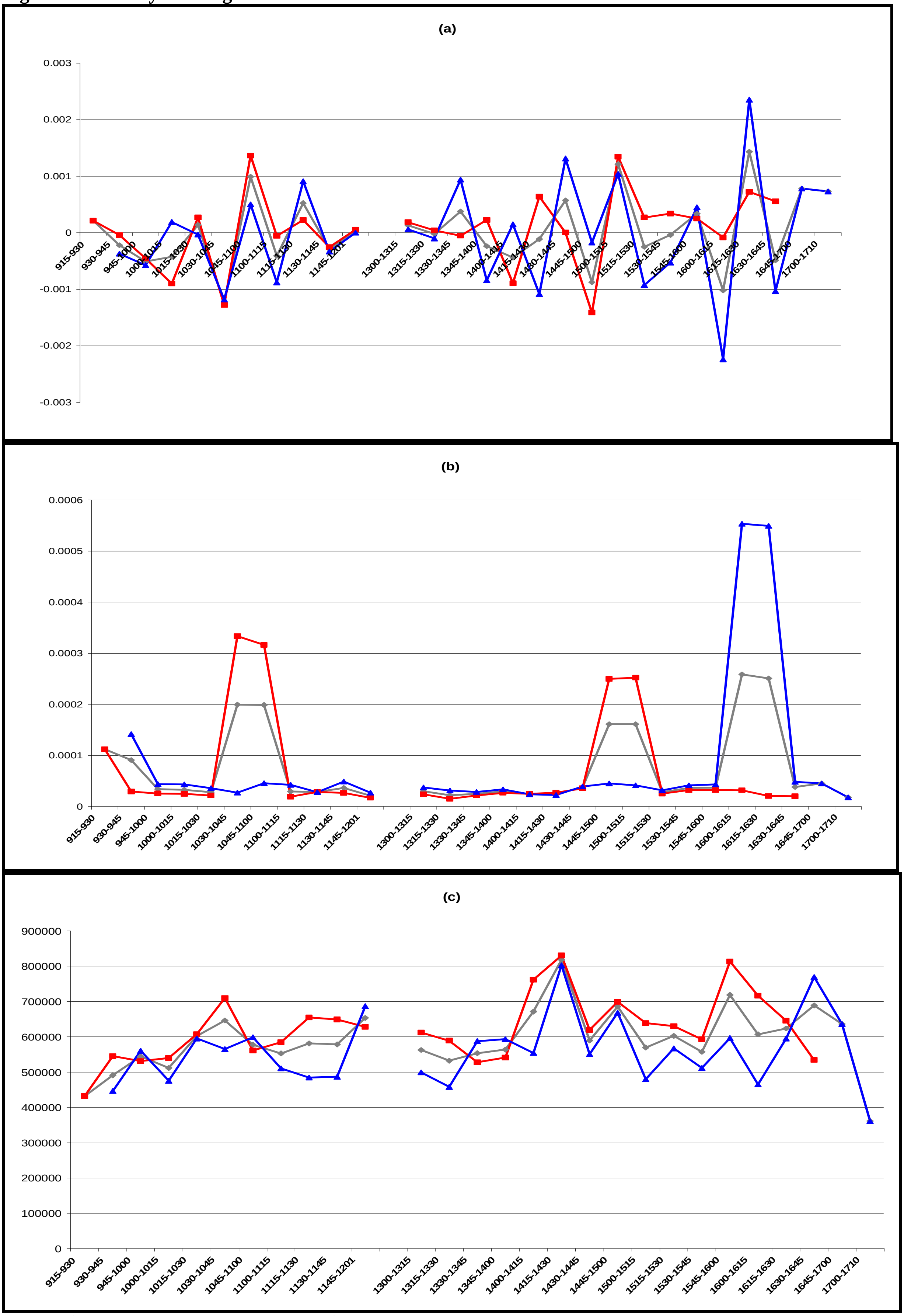
After September 7, 2007, trading hours at TurkDEX were extended from 9:15 a.m.-16:40 p.m. to 9:30 a.m.-17:10 p.m. However, the findings show that the extended hours were not very effective since the trading activity from 16:40 p.m. to 17:10 p.m. is much lower compared to the rest of the day. In addition, volatility is also significantly lower during the extended hours. 16:40 p.m. remains the effective close, even after the trading hours were extended, and this indicates that investors tend to close their positions in derivatives market before the stock market closes. Therefore, a more pronounced spike appears at the end of the trading day. These findings confirm that the period following the opening and immediately before the end of the trading are periods of particular stress and require particular attention. Therefore, the intraday pattern of volatility depicts an inverse relationship with trading volume.

[52] The increase in volatility around the openings of the major markets might also be related to the systematic release of news at that time. For instance, US economic data are typically announced at 8:30 a.m. New York time.

The intraday pattern in trading activity implies that the information content in prices differs in various periods of the trading day. Since information is incorporated into prices at least partly through trading, a period of high trading volume would produce more informative prices than a period of low trading activity. Average trading volume starts with a low level and increases towards the end of the morning session. After the lunch break, the trading volume reaches high levels between 14:15 p.m.-14:30 p.m. and 15:45 p.m.-16:00 p.m., but it continues to fall at the end of the afternoon session. While the trading volume sharply drops at the end of the trading day, the downtrend is higher in post-extension period. As the market closes, traders feel a need to close their positions or rebalance their portfolios before the trading period ends in order to minimize the risk of carrying their positions overnight. However, the evidence is not consistent with the hypothesis that some of the trading activity near the close is driven by the act of redistributing the risks associated with high overnight volatility because trading volume reaches the highest level around 16:00 p.m., a period of one hour before the derivatives market closes.

Consequently, as indicated in Figure 6, there is a negative relationship between trading volume and volatility in the intraday patterns, consistent with the empirical results in previous section. While the intraday trading volume pattern decreases, the volatility increases. This negative relationship between volume and volatility for the emerging markets is supported by the SIAH of Copeland (1976) and Jennings *et al.* (1981). Indeed, it is more likely that in emerging markets, dissemination of information is asymmetric and initially only well-informed traders take positions. After a series of intermediate transient equilibria, a final equilibrium is reached resulting in lower volatility (Girard and Biswas, 2007). Also, the Foucault (1999) model explains that during a period of high uncertainty (high volatility) the trading volume may be reduced by the limit order traders' attitude.

Figure 6: Intraday Trading Patterns



Note: The figures shown above display (a) intraday filtered return, (b) average intraday volatility and (c) intraday average trading volume for each 15-minute interval for ISE-30 index futures.

CHAPTER 8

SUMMARY AND CONCLUSIONS

The derivatives markets have been the most dynamic of all financial markets. The rate of change in derivatives has accelerated in recent years. Volatility estimates are required for efficient pricing of derivative securities as well as for the effective use of these securities in managing and hedging risk. While derivatives markets display high speeds of adjustments, studies based upon daily observations may fail to capture information contained in intraday market movements. Moreover, because of modern communications systems and improved technology, volatility measures based on daily observations ignore critical information concerning intraday price patterns. The timing and frequency of order and trade arrivals carry information on the state of the market and play an important role in market microstructure analysis for the modeling of intraday volatility. The availability of high-frequency datasets and the necessary computing power for their analysis have only become available in the last decade. Recently, there has been a surge of interest among finance scholars to study both empirical market microstructure and the statistical analysis of high-frequency financial data of emerging derivatives markets which play an increasingly important role and shed new light on global financial markets. Despite the importance of high-frequency dataset, the past literature focusing on this topic is still inadequate for emerging derivatives markets.

With the recent steady expansion in most derivatives exchanges in emerging markets, the Turkish derivatives market has exhibited remarkable growth. As high-frequency datasets become available, more accurate models can be derived to benefit from the information embedded in intraday prices of the Turkish Derivatives Exchange, which is an interesting developing financial market to examine. Therefore, this research will improve the understanding of Turkish derivatives market thoroughly and systematically by investigating the time-varying characteristics of most actively-traded and liquid asset, ISE-30 index futures, in order to improve estimation of intraday volatility. It also provides an important opportunity to add to the accumulated evidence to the previous studies by employing intraday dataset. This study contributes to finance literature by filling in some of the major gaps that remain.

The empirical analysis of this study is based on 15-minute intraday ISE-30 index futures data over the period from January 4, 2007 to March 21, 2008. In order to examine the stability of the results, the data set is divided into pre- and post-extension periods consistent with its extended trading hours after September 7, 2007. The results of the statistical analysis will be used to evaluate the empirical evidence in support of the competing theories about the relationship between asset returns and trading volume and to guide the search for appropriate GARCH model specifications in the high-frequency setting.

The gaps identified in this study are of great significance from both academic and empirical perspectives. The primary contribution is that it constitutes the first detailed study of intraday trading patterns behavior of ISE-30 index futures in the Turkish derivatives market, to the best of author’s knowledge. Using a unique dataset, the empirical evidence provides some support for the implications of the model. In particular, the unique behavior associated with this contract regarding the market closure theory[53] is that trading volume is concentrated at the opening and close. This situation may be explained by the absence of trading during the night. The accumulation of information during the evening and at opening can induce trading. Hence, the adjustment of portfolios at the opening gives an intuition of the result. While in pre-extension period futures market began opening 15 minutes earlier than the stock market, in post-extension period the opening sessions for both markets started at the same time. In pre-extension period, investors tended to increase their trading during the early session of the futures market, preceding the opening of the stock market. However, this increase in trading volume was accompanied by a decrease in the return volatility during this opening session. Furthermore, opening session prices during the post-extension period have trading behaviors similar to those of the pre-extension period. On the other hand, the futures market continues to trade for another 10 minutes after the stock market closes for the day, both in pre- and post-extension periods. Trading activity reaches the highest level at the close of the stock market and drops consistently until the close of the futures market. The clustering of trading around the stock market close is due to the desire of investors to exchange their exposure to price changes when the market is closed. The results are also in line with the pertinent theoretical market microstructure literature and the notion that the private information model[54] and the

[53] The model of periodic market closure is presented by Brock and Kleidon (1992) who proposed two explanations for higher transactions demand at the open and the close of the stock exchange. Their first argument explaining the greater demand to trade at open and close concerns the effect of the periodic inability to trade. Their second argument refers to the ability to trade on an alternate market if the primary market is closed.

[54] Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) developed private information microstructure models to analyze intraday volatility patterns. In their models, systematic patterns in volatility appear when there is a convergence of trading activities of both the informed and liquidity traders during certain intervals such as the one just before the market closes or when the market opens.

contagion model[55] play important role while explaining the intraday behavior and trading activity of ISE-30 index futures contract. Private information-based trading increases trading volume, however its effects on volatility is not determinate under stock market closure because the loss of information transmission from the stock market reduces the rise in futures' volatility caused by privately informed trading. Moreover, the contagion model suggests that futures traders make trades according to the information available for stock prices around the stock market close (see Chang *et al.*, 1995; Fong and Frino, 2001). Accordingly, it is to provide evidence that futures market volatility declines when the stock market closes. In sum, the results confirm that reduction in volatility is also consistent with the private information hypothesis and the contagion model. One reasonable explanation for the assertion of the private information hypothesis is that investors can better use their private information during the early trading on the futures market when no activity occurs in the stock market to help reveal the stocks' intrinsic value. On the other hand, the results for the closing session suggest that investors' behavior has not been altered by the stock market closure at the end of the trading day. In addition, the volatility patterns are not associated with times of high volume on the Turkish derivatives market.

Another possible contribution of this paper is the comprehensive analysis of characteristics of high-frequency series and intraday volatility dynamics of the ISE-30 index futures contract using 15-minute time interval subsequences. Various GARCH specifications are proposed in order to provide consistent volatility filters in higher precision for the characteristic of conditionally heteroskedastic data. Although

[55] The contagion model, which was developed by King and Wadhwani (1990), states that trading in one market can affect the price behavior in other related markets because traders' decisions will be influenced by observation of the primary market's price behavior. Therefore, price movements in one market affect those in related markets.

the GARCH methodology has been used extensively in modeling financial time series, index returns in particular, to the authors' best knowledge, a detailed study of application of the GARCH methodology to intraday returns of derivatives in Turkey has not been undertaken. The relative performance of alternative volatility and distribution specifications indicates that the GARCH(1,1) model under GED assumption is found to generate more accurate estimates of high-frequency ISE-30 index futures returns, based on 15-minute intervals data over the asymmetric ones. An empirical estimation of GARCH(1,1) model indicates that the conditional distributions exhibit persistence, with volatility of recent news highly impacting on current volatility of ISE-30 index futures under GED specifications. This finding specifies that volatility reacts quite intensely to market movement; therefore volatilities tend to be more spiky, thus supporting the findings of Alexander (2001). In addition, the phenomenon of the predictive asymmetry of volatility has been examined for intraday returns of the ISE-30 index futures, indicating that the existence of leverage effect is not observed in Turkish derivatives market. While the leverage effect appears important for larger daily or weekly return shocks, it does not seem important for intraday return shocks that are smaller in magnitude. Alternatively, the inability to detect the asymmetric effect in high-frequency data may merely reflect the increased level of noise that creeps in the higher frequency return data.

This study makes also a first attempt to investigate the intraday relationship between volatility and trading volume on ISE-30 index futures at 15-minutes intervals. In line with Tauchen and Pitts (1983), the empirical findings indicate a negative and significant relationship between trading volume and volatility of ISE-30 index futures, suggesting that increases in trading activity lead to a reduction in market volatility. This was attributed to thin trading, which implies that an increase in trading activity causes price transparency and stability. Furthermore, the volatility persistence also remains in intraday return series within each pre- and post-extension period. Thus, the inclusion of trading volume as an explanatory variable in conditional volatility does not reduce volatility persistence, which is consistent with previous studies such as Najand and Yung (1991), Sharma *et al.* (1996), Chen *et al.* (2001), Rahman, *et al.* (2002). These findings help deepen our understanding of the Turkish derivatives markets, which form an important academic topic.

Utilizing data recorded at low frequencies over a prolonged period, ranging from January 4, 2007 through March 21, 2008, and consisting of 2.5 million observations is the last contribution of this study. The dataset is superior to those commonly used in studies of Turkish derivatives market in that it contains all transactions rather than only those which involve a change in price.

8.1. Empirical Implications

High-frequency data provides solid potential to the investors, market participants, policy makers and researchers by facilitating a deeper understanding of financial markets. By using high-frequency data, the behavior of market participants can be investigated contemporaneously as they trade, rather than analyzing their behavior at the end of the day, week or month. Because of the nature of the information flow rate and its integration into markets, the study of the behavior of intraday trading activities in financial markets has become imperative. Safety and transparency, and operational efficiency could be enhanced along proven and successful empirical models helping the derivatives market to become even safer and more efficient. Portfolio managers and other market participants should be aware that returns, volatility and trading volume are simultaneously determined. The significance of intraday trading dynamics of volatility and trading volume would appear to validate the reasoning behind the investment strategy of many market participants, as this wealth of data allows greater insights into the short-term behavior of financial markets.

Volatility of elements such as asset pricing, asset allocation and risk management is a key component of the fundamental problems in modern finance. Therefore, understanding the dynamics of volatility is crucial. Volatility receives a great deal of concern from policy makers and market participants because it is perceived as a measure of risk. Higher volatility in financial markets raises important public policy issues about the stability of the markets and the impact of volatility on the economy. Furthermore, from a theoretical perspective, volatility plays a central role in the pricing of derivative securities.

A better understanding of the relation between volatility and trading volume may help portfolio managers and market participants to get information about derivatives market dynamics. It may help practitioners determine the trend of derivatives prices after extreme events. Price and volatility from one financial asset are also good sources of information to the other financial assets for practitioners. Information from the volatility of ISE-30 index futures is useful in predicting volatilities of the ISE-30 stock index. One important implication is that the derivatives help to make the market more information efficient. This study, therefore, aims to deepen the market's understanding of the above issues while derivatives contribute to market completeness. However, the findings provide convincing evidence that trading volume does not provide valuable information for ISE-30 index future prices.

Portfolio managers should therefore be aware that trading volume itself may not be enough to determine the future index return.

Consequently, a general conclusion on the overall volatility modeling performance suggests that the results are consistent with the theoretical market microstructure literature and carry important implications for portfolio managers and market participants in deriving accurate information about Turkish derivatives market dynamics.

8.2. Future Research

Although this research has unfolded interesting issues on Turkish derivatives market, there are several issues worth further exploration. The results listed above apply only to the ISE-30 index futures data. It would be desirable to expand the sample by including stock market instruments traded in Istanbul Stock Exchange. Although ISE-30 index futures traded in TurkDEX is known as the most actively-traded and liquid asset, research based on ISE-30 stock index traded in ISE may reveal a different picture or they may strengthen the results reported in this study. The relatively narrow applications contained in this research preclude making any general conclusions. Therefore, extending research to include stock market instruments traded in Turkish stock market would appear to be a promising endeavor.

For further research, even more robust results could be attained by expanding the data with the availability of high-frequency data for other emerging derivatives markets. Accordingly, similar tests can be conducted to investigate the intraday volatility dynamics across regions and can be compared with the results of Turkish Derivatives Exchange.

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