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Intraday Volatility in the Turkish Derivatives Market

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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 volatility as well as to highlight the impact of trading volume on intraday volatility specifications. The empirical results show that volatility patterns under Generalized Error Distribution is found to generate more accurate estimates of high-frequency ISE-30 index futures returns. 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: High-Frequency Volatility Modeling, Trading Volume, Turkish Derivatives Market

JEL Codes: G12, G13, G14

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. 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 volatility can be estimated under the diffusion assumption which is often invoked in theoretical studies.

Due to recent developments in the financial markets, derivatives are commonly used for managing various financial risk exposures very efficiently since they allow investors to transfer these risks. On account of the rising significance of emerging countries' financial markets, the motivation to employ 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.

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Turkish capital market finally acquired the long-awaited instruments when it introduced futures trading on its newly established Turkish derivatives market in 2003. As Turkish Derivatives Exchange (TurkDEX hereafter) 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 instrument at the TurkDEX[1]. 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 model as well as highlighting the impact of the trading volume on the volatility specifications.

The contribution of this paper to the related literature is three-fold. First, it represents the comprehensive analysis of intraday volatility dynamics of the ISE-30 index futures contract using 15-minute time interval subsequences. In addition, alternative distributions possessing such characteristics have been proposed to better account for the deviations from normality in the conditional distributions of returns. Second, 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 GARCH specification may shed further light on the information asymmetry and volatility clustering in the market which carries important implications for market efficiency. Finally, it uses a very comprehensive data set ranging from January 4, 2007 through March 21, 2008, which consists of 2.5 million observations. 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.

The rest of the paper is organized as follows. The following section provides a brief literature on modeling of volatility using high-frequency data. Section 3 outlines the econometric methodology. The data set are presented in Section 4 followed by the empirical results. Finally, section 6 contains concluding remarks.

2. Literature Review

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. While the early empirical studies[2] concentrated on the equity market either focused on the US or other developed stock markets, concentration has been directed in recent years towards intraday regularities in the markets for foreign exchange, financial and commodity futures in emerging countries.

Ho and Lee (1998) analyzed the intraday trading pattern of the index futures market in Hong and 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. Cheng and Cheng (2000) and Fong and Frino (2001) evaluated whether the longer trading hours of the Hang Seng Index Futures (HSIF) market would lead to a change in the volatility in the cash and futures markets. 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. Additionally, 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.

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. Tezölmez (2000) examined the intraday return and volatility patterns as well as the effect of information release on these. Finally, Küçükkocaoglu (2003) examined the behavior of the intra-daily stock returns and day-end stock price manipulation in the ISE and found that stock prices systematically rise towards the closing minute and the last trade is more often initiated by a buyer.

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. 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. 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. Chang *et al.* (2006) and Sioud *et al.* (2006) investigated the intraday patterns of trading volume, volatility, and spreads on the Taiwan Futures Exchange and Tunisian Stock Exchange, respectively. They found that trading volume exhibited U-shaped pattern over the continuous session for all days of the week.

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. 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.

3. Methodology

This study makes use of intraday transaction data of ISE-30 index futures contract provided by Matriks[4] database and covers the period from January 4, 2007 through March 21, 2008. The prices are 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[5].

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..

Consecutively, two changes were made to the trading hours on the TurkDEX. 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.. 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.

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:

$$\ln vf_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \varepsilon_t \quad (1)$$

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.

The descriptive statistics of intraday ISE-30 index futures series are represented in Table 1. The sample average return of -0.74x10^{-4}% appears indistinguishable from zero given the sample standard deviation of 0.85%. The distribution is positively skewed, implying that 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 is larger than three for return and volatility series which suggest that the distribution is leptokurtic. The observed leptokurtosis may be due to heteroskedasticity in the data, which may be captured with the GARCH model. However, the kurtosis for trading volume is less than three, which suggests that detrended volume has the platykurtic distribution. 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. The test statistics for up to 50th order serial correlation are illustrated in Table 1. 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 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. 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 1: Descriptive Statistics of 15-minutes ISE-30 Index Futures Series

Data	Mean	*SD*	Skew.	Kurtosis	*JB*	$Q(50)$	$Q_2(50)$
04.01.2007-21.03.2008							
Return	-0.74×10^{-6}	0.0085	-0.1015	403.44	59.13×10^{6}* (0.000)	1508.15* (0.000)	2198.4* (0.000)
Volatility	0.73×10^{-4}	0.0015	40.755	1736.16	1110.3×10^{6}* (0.000)	2198.40* (0.000)	2207.9* (0.000)
Volume	-1.07×10^{-15}	1.2139	0.2216	2.4733	174.79* (0.000)	61.91 (0.122)	144.59* (0.000)
04.01.2007-06.09.2007 (Pre-extension Period)							
Return	0.47×10^{-4}	0.0082	-0.0124	390.42	3.14×10^{7}* (0.000)	916.00* (0.000)	1228.8* (0.000)
Volatility	0.68×10^{-4}	0.0013	35.813	1309.8	3.54×10^{8}* (0.000)	1228.84* (0.000)	1230.1* (0.000)
Volume	-0.049	1.2395	0.2079	2.5005	87.037* (0.000)	61.92 (0.120)	108.79* (0.000)
07.09.2007-21.03.2008 (Post-extension Period)							
Return	-0.61×10^{-4}	0.089	-0.1883	405.32	2.67×10^{7}* (0.000)	644.69* (0.000)	970.39* (0.000)
Volatility	0.79×10^{-4}	0.0016	43.720	1921.9	6.02×10^{8}* (0.000)	970.39* (0.000)	975.75* (0.000)
Volume	0.0062	1.1806	0.2429	2.4169	93.761* (0.000)	40.21 (0.837)	66.42** (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 $Q_2(50)$ 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. *, ** denote statistical significance at 1% and 10% level.

To investigate the intraday seasonality of returns and volatility and the reasons for lack of independence (see Table 1), the autocorrelation functions 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[6]. 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. According to the autocorrelation functions of returns and volatility, 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 1, it is obvious that taking into account 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".

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

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. 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.

$$\sigma_{t}^{2} = \alpha_0 + \alpha_1 \varepsilon_{i-1,t}^{2} + \beta_1 \sigma_{i-1,t}^{2} + \psi V_{i,t} \qquad (2)$$

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, 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. Empirical Results

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, Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1981) and KPSS (Kwiatoski *et al.,* 1992) tests. Table 2 represents the results of the unit root tests for return and deterended 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. 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 (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.

Table 2: 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); which 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 3 indicates the results of fitting restricted AR(2)-GARCH(1,1) process under the assumption of Gaussian distribution and GED[7] to the 15-minute ISE-30 index futures return series for the sample period. Consistent with most financial data, with a few exceptions, most of the parameter estimates of the AR(2)-GARCH(1,1) model with GED[8] 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. As shown in Table 3, 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 "spiky" volatility. Therefore, this study indicates that the Turkish derivatives market reacts somewhat more to recent news which is consistent with Alexander (2001).

The persistence in volatility as measured by sum of α_1 and β_1 in GARCH(1,1) model under the assumption of GED is closer to unity for ISE-30 index futures returns for each period. 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 and it is significant at any level. 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.

Table 3: 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	$-2.77*10^{-8}$ ($3.40*10^{-6}$)	$7.02*10^{-5}$ ($4.65*10^{-5}$)	$3.78*10^{-6}$ ($7.16*10^{-6}$)	$7.35*10^{-5}$ ($6.36*10^{-5}$)	$-1.39*10^{-9}$ ($2.18*10^{-6}$)	$6.91*10^{-5}$ ($8.73*10^{-5}$)
η_1	-0.05391* (0.0055)	-0.2299* (0.0140)	-0.0820* (0.0055)	-0.2770* (0.0191)	$-1.08*10^{-5}$ (0.0018)	-0.1811* (0.0211)
η_2	$3.06*10^{-5}$* (0.0021)	-0.0541* (0.0121)	-0.0079** (0.039)	-0.0644* (0.0170)	$-2.26*10^{-7}$ (0.0007)	-0.0500** (0.0201)
			Variance Equation			
α_0	$8.31*10^{-6}$ ($4.67*10^{-7}$)	$1.00*10^{-5}$* ($2.50*10^{-7}$)	$1.08*10^{-5}$* ($8.51*10^{-7}$)	$7.73*10^{-6}$* ($3.74*10^{-7}$)	$9.22*10^{-6}$* ($7.67*10^{-7}$)	$1.17*10^{-5}$* ($3.58*10^{-7}$)
α_1	0.6672* (0.0572)	0.2596* (0.0141)	0.8061* (0.1092)	0.2291* (0.0207)	0.6357* (0.0780)	0.2905* (0.0215)
β_1	0.3177* (0.0222)	0.4354* (0.0136)	0.1929* (0.0357)	0.5117* (0.0221)	0.3376* (0.0306)	0.4004* (0.0181)
ς	0.6378* (0.0061)	1.5*	0.5754* (0.0085)	1.5*	0.6648* (0.0100)	1.5*
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 occurrence of time-dependent conditional heteroscedasticity could be due to the arrival of news and irregular information. Especially 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 trading volume into the conditional variance equation.

Table 4 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 GED. 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[9], the inclusion of trading volume in the conditional variance equation results in a substantial reduction of volatility persistence. For emerging markets, this evidence is weaker[10]. 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 are moderately consistent with the Sequential Information Arrival Hypothesis[11] (SIAH) of Copeland (1976) and Jennings *et al.* (1981). All verify the existence of an inverse relationship between volatility and volume dynamics.

An 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. 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 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.

Table 4: 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	$-1.94*10^{-4}$ (0.0002)	$-1.15*10^{-4}$ (0.0002)	$1.29*10^{-5}$ ($4.66*10^{-5}$)	$-1.17*10^{-4}$ (0.0002)	$-4.35*10^{-4}$** (0.0002)	$3.60*10^{-5}$ ($5.93*10^{-5}$)	$-1.30*10^{-5}$ (0.0003)	$-9.82*10^{-5}$ (0.0003)	$-9.27*10^{-5}$ (0.0002)
η_1	-0.4807* (0.0288)	-0.4820* (0.0291)	-0.2688* (0.0137)	-0.5026* (0.0409)	-0.5027* (0.0407)	-0.2644* (0.0182)	-0.4601* (0.0422)	-0.4599* (0.0419)	-0.4592* (0.0313)
η_2	-0.1872* (0.0312)	-0.1869* (0.0314)	-0.0797* (0.0120)	-0.1872* (0.0436)	-0.1872* (0.0437)	-0.0570* (0.0154)	-0.1881* (0.0479)	-0.1881* (0.0475)	-0.1877* (0.0337)
α_0	$4.25*10^{-5}$* ($1.10*10^{-6}$)	$4.24*10^{-5}$* ($1.61*10^{-6}$)	$8.84*10^{-6}$* ($3.64*10^{-8}$)	$3.58*10^{-5}$* ($3.36*10^{-6}$)	$3.52*10^{-5}$* ($3.24*10^{-6}$)	$9.34*10^{-6}$* ($3.97*10^{-7}$)	$4.85*10^{-5}$* ($5.01*10^{-6}$)	$4.81*10^{-5}$* ($5.49*10^{-6}$)	$3.87*10^{-5}$* ($4.38*10^{-6}$)
α_1	0.1451* (0.0166)	0.1491* (0.0162)	0.2595* (0.0108)	0.1508* (0.0202)	0.1512* (0.0206)	0.2457* (0.0198)	0.1480* (0.0242)	0.1475* (0.0253)	0.1472* (0.0284)
β_1	0.5962* (0.0124)	0.5979* (0.0116)	0.4864* (0.0041)	0.5983* (0.0335)	0.5973* (0.0347)	0.4211* (0.0219)	0.5928* (0.0436)	0.5906* (0.0443)	0.5869* (0.0480)
ψ	$-1.64*10^{-5}$* ($3.06*10^{-7}$)	$-1.64*10^{-5}$* ($4.00*10^{-7}$)	$-2.93*10^{-6}$* ($1.12*10^{-8}$)	$-1.38*10^{-5}$* ($5.38*10^{-7}$)	$-1.36*10^{-5}$* ($5.32*10^{-7}$)	$-2.83*10^{-6}$* ($6.23*10^{-8}$)	$-2.02*10^{-5}$* ($2.58*10^{-7}$)	$-1.99*10^{-5}$* ($6.83*10^{-7}$)	$-1.59*10^{-5}$* ($2.98*10^{-7}$)
ς		1.9928* (0.0095)	1.5*		1.9885* (0.0128)	1.5*		1.9929* (0.0153)	1.5*
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.

5. Conclusion

This paper generates a comprehensive analysis of intraday volatility dynamics of the ISE-30 index futures contract using 15-minute time interval subsequences. Results 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. 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).

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 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. 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.

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.

Endnotes

1. 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 2010, the trading volume of ISE-30 index futures contract reached $278 billion representing 97% 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 74 million contracts in 2010. (www.turkdex.org.tr)

2. Wood et al. (1985), Harris (1986), Jain and Joh (1988), Foster and Viswanathan (1993), Mian and Adam (2001), Ozenbas et al. (2002)

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

4. 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.

5. The computer program used for this purpose is based on the MATLAB.

6. The result is not reported, but is available from the author upon request.

7. When using GED distributions, the scale parameter 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.

8. 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.

9. Lamoureux and Lastrapes (1990), Andersen (1996), Gallo and Pacini (2000) in the US, Omran and McKenzie (2000) in the UK, Pyun et al. (2000) in Korea, Bohl and Henke (2003) in Poland.

10. Huang and Yang (2001) in Taiwan, Wang et al. (2005) in China, Baklacı and Kasman (2006) in Turkey.

11. 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.

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