AN EMPIRICAL ANALYSIS OF TRADING VOLUME AND RETURN VOLATILITY RELATIONSHIP IN THE TURKISH STOCK MARKET

Assistant Professor, Hasan BAKLACI
Department of International Trade and Finance, Faculty of Economics and Administrative Sciences,
hasan.baklaci@ieu.edu.tr

Associate Professor, Adnan KASMAN
Department of Economics, Faculty of Business,
adnan.kasman@deu.edu.tr

ÖZET

Bu çalışmada, 1998-2005 dönemi günlük veriler kullanılarak Türk hisse senedi piyasasında işlem gören 25 hisse senedi için işlem hacmi ve getiri volatilitesi ilişkisi incelenmiştir. Çalışma sonuçları, diğer birçok çalışma bulguları ile paralellik gösterecek şekilde, işlem hacminin Türk hisse senedi piyasasında hisselerin getiri volatilite süreçlerini anlamlı bir şekilde etkilediğini göstermektedir. Öte yandan, sonuçlar, aynı zamanda, işlem hacminin birçok hisse senedinin volatilite sürekliliğinin azalmasında önemli bir etkisi olmadığını da ortaya koymaktadır. Bu sonuç, Türk hisse senedi piyasasında "Karışık Dağılımlar Hipotezi"nin geçerli olmadığına işaret etmektedir. Elde edilen sonuçlar, Türk hisse senedi piyasası da dahil olmak üzere, gelişmekte olan ülkelerde yapılan birçok çalışma sonucu ile tutarlılık göstermektedir.

ABSTRACT

This paper investigates the volume-return volatility relationship for 25 individual stocks in the Turkish stock market, using daily data for the period 1998-2005. The results indicate that trading volume significantly contributes to the return volatility process of stocks in Turkish stock market, as suggested in many studies. On the other hand, the results also signify that the trading volume has no significant effect on the reduction of the volatility persistence for majority of stocks in the sample, challenging the presence of "Mixed Distribution Hypothesis" in Turkish stock market. These results are consistent with the empirical findings of a number of studies in emerging markets, including with those done in Turkish stock market.

INTRODUCTION

As a primary risk factor, the volatility characteristics of stock returns have been one of the key topics examined in finance literature. Numerous studies on this subject have found significant support in favor of the existence of conditional variance in stock returns. Although there is no a clear-cut consensus regarding the underlying rationale for the ARCH and GARCH effect in stock returns, one of the predominant theoretical justifications has been the mixture of distributions hypothesis (MDH hereafter). MDH, as put forward by Clark (1973), Tauchen and Pitts (1983), and Lastrapes and Lamoureux (1990), alleges that the conditional heteroscedasticity in stock returns can be explained by a serially correlated mixing variable that measures the rate at which information is transmitted to the market. These authors have shown that the information arrivals stemming from the existence of exogenous variables can be identified by the mixture of distributions, and that these variables exhibit time-varying ARCH effect.

In many of the later studies investigating the validity of MDH in various stock markets, the trading volume is taken as a proxy to represent the rate and bulk of information flow to the market. As initially suggested by Morgan (1976), volume is regarded as a major risk factor contributing to the volatility of returns, particularly in less liquid and thin markets including emerging markets. Most studies on the relationship between return volatility and trading volume include predominantly the developed markets. There is a scant literature on this topic in emerging markets, although there is a noticeable progress in the amount of studies in these market segments in recent years (see Bohl and Henke, 2003; Ahmed, Hassan and Nasir, 2005)

This paper aims to contribute to the literature by investigating the relationship between trading volume and stock return volatility in Istanbul Stock Exchange (ISE) by utilizing a relatively more recent database and extensive dataset including individual stocks instead of a general index which has been primarily used in previous studies.

The paper is structured as follows: Section 2 provides a brief review of literature. Section 3 discusses econometric methodology. The data set and empirical results are presented in Section 4. Finally Section 5 contains concluding remarks.

LITERATURE REVIEW

It is well documented that financial time series, particularly the volatility of returns in financial assets exhibit time varying conditional variance characteristic which is implied in a GARCH model set forth by Bollerslev (1986). The power of GARCH modeling lies in its effectiveness in capturing volatility clustering and persistence. Hence, ARCH and GARCH modeling is widely used in forecasting the time-dependent volatility characteristics of many financial assets. Furthermore, an ARCH specification not only allows the identification of volatility clustering in an autoregressive structure but also allows a mixture of distributions, such as daily stock returns, being generated by a dominant stochastic mixing variable. In many cases, the rate of information flow is considered as the primary mixing variable.

Depending on this basic premise, MDH states that the time-varying volatility pattern in stock returns can be attributed to time-varying rate of news arrivals about a particular stock. An increase in the amount of information leads to a divergence in the interpretation. Brock and LeBaron (1996) argued that when demand diversity reflected in trading process and volume is stronger, the volatility persistence of returns arise from beliefs rather than fundamentals. Accordingly, more investors have an incentive to trade the share based on diverse expectations on future returns. Based on this argument, GARCH behavior in stock's return is generated by a serially correlated news arrival process where arrivals can be proxied by the trade volume.

Many studies have verified that the trading volume significantly contributes to the time-series return process of stocks. As such, McKenzie and Faff (2003), have shown that the conditional autocorrelation in stock returns is highly dependent on trading volume for individual stocks but not for the index, reflecting the fact that liquidity disparities for stocks has a significant impact at individual level but not at aggregate level. Lamoureux and Lastrapes (1990, 1994) have conducted one of the pioneer studies on testing the validity of MDH by deriving a GARCH model and by using the trading volume as a proxy for the rate of daily information arrival. They have concluded that the volatility persistence diminishes by including trading volume in the conditional variance equation of stock returns.

Likewise, Brailsford (1994), using Australian equities, has documented that there is a significant reduction in volatility persistence after accounting for the trading volume as a proxy for the rate of information arrival. Similar results are achieved in various studies using different countries. To name a few, Bohl and Henke (2003) in Poland, Gallagher and Kiely (2005) in Ireland, Pyun, et al. (2000) in Korea, Wang, et al.(2005), and Gallo and Pacini (2000) in theU.S. have all concluded that trading volume, serving as an appropriate proxy for information, significantly reduces the volatility persistence in those countries. In contrast, Ahmed, et al.(2005) in Malaysia, Huang and Yang (2001) in Taiwan, Salman (2002) and Yuksel (2002) in Turkey, and Chen, et al. (2001) in nine developed markets have all concluded that persistence in return volatility remains even after volume is included in conditional variance equation; results in conflict with MDH.

Regarding other few studies including Turkish stock market, Guner and Onder (2002) have found out a significant relationship between volatility and trading volume. Specifically, they have found out that even though higher volatility is associated with low volume stocks in general, for morning session, high volume stocks also exhibit high volatility stemming from the intensity of information-based trading for high volume stocks in stock market opening.

Gunduz and Hatemi (2005) and Basci et al.(1996) determined that there is a cointegrating relationship between stock price changes and volume in Turkish stock market indicating a long-term relationship between these variables resulting from the information based effect of volume on price changes as well as the encouraging impact of positive price changes on trading volume figures.

Sabri (2004) has discovered that trading volume represent one of the main factors in predicting return volatility for Turkey and other emerging markets used in the sample.

Using a modified MDH, in which the model assumes a volume equation with conditional Poisson distribution rather than conditional normal distribution as suggested by standard MDH, Andersen (1996) has pointed out that a the normality restriction imposed by standard MDH as well as finite sample biases might bias volatility persistence measures downward. He has further asserted that a modified MDH specification taking these factors into account outperforms standard MDH.

The asymmetric impact of volume on return volatility through price formation process is also well documented in literature. Admati and Pfleiderer (1988) denote that when the liquidity traders choose to trade at the same time of the day, this pooling of trades attracts informed traders. This strategy, in turn, minimizes the adverse selection costs reflected in bid-ask spreads. More specifically, they show that in intraday transactions, high volume periods are associated with low trading costs and return volatility. On the other hand, Foster and Viswanathan (1993) report quite contradictory results specifying that high adverse selection costs and thus higher return volatility are found at times of the day with higher trading volume. They further argue that the effect of volume on return volatility exhibit a U-shaped pattern. Specifically, the effect is very high in the first half hour of trading, fall during the mid-day and then increases again towards the close of trading.

The impact of asymmetric information on intraday volume-volatility relation is also well pronounced in He and Wang (1995). Their findings indicate that the intraday time-series characteristic of volume- volatility pattern is closely related to the flow (exogenous or endogenous) and to the nature of information (private or public). In their model, exogenous information included new private signals and public announcements and endogenous information included only public information. They have demonstrated that private information generates trade volume both in current and also future periods whereas public information generates volume only in current periods. Moreover, they have revealed that exogenous information leads to higher price changes and volatility when compared with endogenous information.

Stoll and Whaley (1990), as well, have unveiled the volatility-volume irregularities in a more extensive study. Their results show that the ratio of daytime return volatility to overnight volatility is greater than one and the ratio is smallest for lowest-volume stocks. They attribute this difference to the fact that the low-volume stocks have greater overnight volatility related to the presence of more private information revealed through trading for these stocks, leading to a greater volatility at the open. Jones, Kaul and Lipson (1994) argue that the size of trades or volume has a significant effect on return volatility for only small firms. They further contend that the size of trades has no information content beyond that contained in the number of transactions.

As a summary, majority of the studies have confirmed the existence of a significant volume and return volatility relationship although in mixed forms and patterns. However, concerning emerging markets, even though there is a progress in recent years, the literature still suffers from the scarcity of studies inspecting the return volatility-volume relationship in these market segments, particularly for Turkey. Besides, most of the existing studies on emerging markets and those conducted in Turkey have used solely stock index instead of individual stocks. This particular study aims to fill this gap by investigating the impact of trading volume on volatility persistence and the validity of MDH for 25 stocks traded in ISE.

METHODOLOGY

As mentioned in the previous section, several hypotheses have been attempted to explain the behavior of asset returns since the seminal work by Engle (1982). The mixed distribution hypothesis (MDH) provides one plausible explanation, and states that daily returns seem to be generated by a mixed distribution. In particular, the rate of daily information arrivals can be viewed as a generating process by the stochastic mixing variable. Hence, an appropriate model from ARCH family can capture the time series properties of such mixing variables. In this model, the return over the full trading day, r_t, is the sum of $i = 1,2,.....n_t$ intraday equilibrium returns δ_i

$$r_t = \sum_{i}^{n_t} \delta_{it}$$
(1)

Where the random variable n_t is the mixing variable. Hence, the rate of information flow into a market during a given day is considered to be stochastic. δ_{it} is independently and identically distributed with mean zero and variance σ^2, $N(0,\sigma^2)$. Since the number of intraday returns is random, daily returns follow a mixture of normals with n_t as the mixture variable. Eq. (1) states that daily returns are generated by a subordinated stochastic process in which r_t is subordinate to δ_i and n_t is the directing process (see Lamoureux and Lastrapes, 1990). For a sufficiently large sample where n_t and δ_i are independently and identically distributed, the Central Limit Theorem implies $r_t \mid n_t \sim N(0,\sigma^2 n_t)$. Next, following Lamoureux and Lastrapes (1990), we assume that the number of information arrivals follows an autoregressive process

$$n_t = \alpha + \theta(L)n_{t-1} + \varepsilon_t$$
(2)

Where α is a constant, $\theta(L)$ is a polynomial in the lag operator L and ε_t represents the error term. The conditional variance of the daily return r_t is defined as following

$$\sigma^2_{r_t|n_t} = E(r_t^2 \mid n_t) = \sigma_t^2 n_t$$
(3)

and substituting the autoregressive process of (2) into (3) yields

$$\sigma^2_{r_t|n_t} = \sigma^2\alpha + \theta(L)\sigma^2_{r_{t-1}|n_{t-1}} + \sigma^2\varepsilon_t \qquad (4)$$

Eq. (4) represents the persistence in terms of conditional variance that can be estimated by a GARCH model. Since the relationship between daily return variance and the unobservable mixing variable cannot be easily estimated, a proper proxy is required. The trading volume could serve as a proxy measure for the unobservable amount of information that flows into the market (see Andersen, 1996; Lamoureux and Lastrapes, 1990).

The existence of autocorrelation in the volume time series is essential because the MDH implies that serial correlation in volume causes conditional heteroscedasticity in stock returns. Following Bohl and Henke (2003), the serial correlation structure of trading volume is analyzed using autocorrelation coefficients and Ljung-Box statistics. Then the stationarity of trading volume is tested using ADF and KPSS tests. Testing unit root is important because subsequent tests for the impact of trading volume on volatility may be invalid if the trading volume series are nonstationary.

Following model is used to test the impact of trading volume on volatility

$$r_t = \alpha_0 + \alpha_1(L)r_{t-1} + \varepsilon_t \qquad (5)$$

and

$$\sigma_t^2 = \beta_0 + \beta_1(L)\varepsilon^2_{t-1} + \beta_2(L)\sigma^2_{t-1} + \beta_3 V_t$$
(6)

Where $\alpha_1(L)$, $\beta_1(L)$, and $\beta_2(L)$ represent polynomials in the lag operator L and V_t is the trading volume. As seen in Eq. (5), an autoregression in the mean of returns is allowed. Therefore, the possibility of a low-order linear autoregressive process in returns of the individual stocks is taken into account.

The conditional variance is modeled in Eq. (6), including the daily total volume of stocks traded, V_t from close t-1 to close of t as a proxy of information arrivals. First, we estimated a restricted version of Eq. (6) by setting the coefficient of the volume of trade to zero, $\beta_3 = 0$. If the parameters of the lag polynomials $\beta_1(L)$, and $\beta_2(L)$ are positive, then volatility shocks persist over time where the degree of persistence is determined by the magnitude of these parameters. Second, we estimate the unrestricted version of Eq. (6). If the trading volume represents a reasonable proxy for information arrival and is serially correlated, estimation based on Eq. (5) and Eq. (6) would yield $\beta_3 > 0$ and values of $\beta_1(L)$, and $\beta_2(L)$

are significantly smaller than that when V_t is not included. Hence, the mixing variable is statistically significant in explaining the volatility of stock returns.

As stated in previous section, our objective is to examine whether inclusion of serially correlated proxy, namely the trading volume, diminish the values of $\beta_1(L)$, and $\beta_2(L)$ significantly for a sample of stocks traded in the Turkish stock market.

DATA AND EMPIRICAL RESULTS

Data

The dataset is comprised of daily return and volume series of 25 stocks and sub-indices traded in ISE. The sample period spans from January 1998 to July 2005. The individual stocks in the sample are comprised of firms with different size and trading volume. The rationale behind mixing firms with different characteristic is to see if the results obtained from the return volatility-volume analysis vary across firms with different trading volume. The list of firms included in the sample are provided in Appendix 1.
The stock returns are calculated by the following formula:

$$r_t = \ln(p_t / p_{t-1}) \quad (7)$$

Where p_t represents the end-of-day closing price of the individual stock. Table 1 reports the descriptive statistics or daily stock returns of individual firms. The examination of the results in Table 1 indicates that the mean returns of all individual stocks except for Menderes Tekstil are positive. The mean returns ranges between -0.055% and 0.182% and the standard deviation between 2.72% and 12.51%. The Jarque–Bera statistic indicates that the distribution of returns of all sample stocks has fat tails and sharper peaks than the normal distribution. Also, all return series exhibit excess kurtosis, which is consistent with the presence of GARCH effects.

Table 1. Descriptive statistics for stock returns of individual firms
Note: The table reports mean, standard deviation, skewness, kurtosis, the Jarque-Bera (JB) test for normality. The values in parantheses are the p-values.

Stock	Mean(%)	Stdev(%)	Skewness	Excess Kurtosis	JB
AFYON	0.176	3.327	0.293	6.450	926.86 (0.000)
AKBANK	0.144	3.827	0.226	6.178	793.59 (0.000)
AKGRT	0.142	3.955	-0.201	6.069	742.43 (0.000)
AKSUE	0.055	4.129	0.674	9.347	2414.2 (0.000)
ARCLK	0.141	12.509	0.125	5.618	536.57 (0.000)
BAGFS	0.076	3.857	0.178	7.239	1403.7 (0.000)
BEKO	0.116	3.970	0.132	5.821	622.68 (0.000)
BRISA	0.115	3.657	0.133	6.356	878.32 (0.000)
BUCIM	0.168	2.730	1.022	11.576	602.39 (0.000)
DGZTE	0.067	4.897	0.288	5.224	409.88 (0.000)
DOGHOL	0.129	4.646	0.088	4.893	280.84 (0.000)
ECİLC	0.179	4.142	0.264	5.839	646.17 (0.000)
EGGUB	0.176	4.151	0.354	7.308	1477.4 (0.000)
EREGLİ	0.129	3.940	0.057	5.968	683.71 (0.000)
FİNBN	0.182	4.311	-0.119	5.519	492.41 (0.000)
FROTO	0.143	3.996	0.167	5.679	565.25 (0.000)
GARANTİ	0.146	5.018	0.229	32.118	658.34 (0.000)
GARGYO	0.124	4.339	0.410	7.159	1353.2 (0.000)
KOÇHOL	0.090	3.898	0.162	5.271	408.20 (0.000)
KRDMA	0.078	5.364	0.502	6.213	806.25 (0.000)
MENDRS	-0.055	4.087	-0.076	7.947	1263.7 (0.000)
MMART	0.110	4.489	0.268	6.314	874.10 (0.000)
SAHOL	0.122	3.771	0.227	5.956	693.41 (0.000)
TCELL	0.010	3.925	0.048	6.501	635.36 (0.000)
TUBORG	0.098	3.978	0.348	7.234	1428.7 (0.000)

Table 2 reports autocorrelation coefficient of up to three lags, Q (20), augmented Dickey-Fuller test statistics, and KPSS unit root test statistics for the individual trading volume series (Since the null hypothesis in Augmented Dickey–Fuller test is that a time series contains a unit root, this hypothesis is accepted unless there is a strong evidence against it. However, this approach may have low power against stationary near unit root processes. In contrast, Kwiatkowski, Phillips, Schmidt, and Shin (1992) present a test where the null hypothesis is that a series is stationary. The KPSS test complements the Augmented Dickey–Fuller test and concerns regarding the power of either test can be addressed by comparing the significance of statistics from both tests. A stationary series has significant Augmented Dickey–Fuller statistics and insignificant KPSS statistics

According to Kwiatkowski et al. (1992), the test of KPSS assumes that a time series can be composed into three components, a deterministic time trend, a random walk and a stationary error term: $y_t = \delta t + r_t + \varepsilon_t$, where r_t is a random walk $r_t = r_{t-1} + u_t$. The u_t is iid $(0, \sigma_u^2)$). As shown in the table all series exhibit significant serial correlation. Hence, for the sample stocks, the rate of information arrival, measured by the trading volume is significantly serially correlated. The test statistics of both unit root tests are statistically significant at one percent level, indicating that all sample series are stationary.

Table 2. Autocorrelation coefficients of individual stock returns and results of unit root tests.

Stock	Lag(1)	Lag(2)	Lag(3)	Q(20)	ADF	KPSS
AFYON	0.805 (0.000)	0.763 (0.000)	0.747 (0.000)	0.583 (0.000)	-3.607	0.984
AKBANK	0.748 (0.000)	0.659 (0.000)	0.618 (0.000)	0.483 (0.000)	-4.864	1.113
AKGRT	0.618 (0.000)	0.453 (0.000)	0.387 (0.000)	0.188 (0.000)	-6.574	0.806
AKSUE	0.743 (0.000)	0.661 (0.000)	0.621 (0.000)	0.441 (0.000)	-4.320	0.825
ARCLK	0.680 (0.000)	0.558 (0.000)	0.550 (0.000)	0.238 (0.000)	-6.866	0.857
BAGFS	0.752 (0.000)	0.676 (0.000)	0.645 (0.000)	0.399 (0.000)	-5.518	2.118
BEKO	0.755 (0.000)	0.646 (0.000)	0.592 (0.000)	0.353 (0.000)	-7.540	0.773
BRISA	0.728 (0.000)	0.653 (0.000)	0.579 (0.000)	0.447 (0.000)	-4.723	0.855
BUCIM	0.433 (0.000)	0.353 (0.000)	0.348 (0.000)	0.216 (0.000)	-6.332	0.810
DGZTE	0.722 (0.000)	0.611 (0.000)	0.562 (0.000)	0.282 (0.000)	-6.345	1.248
DOGHOL	0.785 (0.000)	0.697 (0.000)	0.655 (0.000)	0.492 (0.000)	-4.867	2.742
ECİLC	0.700 (0.000)	0.603 (0.000)	0.543(0.000)	0.282 (0.000)	-6.752	1.312
EGGUB	0.724 (0.000)	0.629 (0.000)	0.597 (0.000)	0.379 (0.000)	-5.828	1.294
EREGLİ	0.370 (0.000)	0.308 (0.000)	0.280 (0.000)	0.041 (0.000)	-9.749	1.005
FİNBN	0.832 (0.000)	0.764 (0.000)	0.730 (0.000)	0.614 (0.000)	-3.776	2.388
FROTO	0.718 (0.000)	0.631 (0.000)	0.589 (0.000)	0.413 (0.000)	-4.458	2.461
GARANTİ	0.625 (0.000)	0.577 (0.000)	0.575 (0.000)	0.354 (0.000)	-5.769	1.389
GARGYO	0.660 (0.000)	0.624 (0.000)	0.582 (0.000)	0.275 (0.000)	-6.674	1.262
KOÇHOL	0.632 (0.000)	0.526 (0.000)	0.461 (0.000)	0.279 (0.000)	-6.468	2.013
KRDMA	0.784 (0.000)	0.714 (0.000)	0.676 (0.000)	0.473 (0.000)	-5.013	1.431
MENDRS	0.801 (0.000)	0.729 (0.000)	0.695 (0.000)	0.531 (0.000)	-3.797	2.282
MMART	0.784 (0.000)	0.721 (0.000)	0.680 (0.000)	0.521 (0.000)	-4.052	3.639
SAHOL	0.646 (0.000)	0.513 (0.000)	0.436 (0.000)	0.227 (0.000)	-6.267	0.747
TCELL	0.728 (0.000)	0.646 (0.000)	0.599 (0.000)	0.393 (0.000)	-5.139	0.764
TUBORG	0.726 (0.000)	0.636 (0.000)	0.582 (0.000)	0.388 (0.000)	-4.980	0.858

Note: Autocorrelation coefficients contain up to three lags and Q(20), and the p-values are reported in parentheses. The ADF and KPSS tests contain a constant term and augmentations of DF tests are determined according to the AIC. Critical values of ADF and KPSS tests at one percent level are -3.433 and 0.739, respectively.

Empirical Results

To check for possible autoregressive effects in the mean of daily returns, Eq. (5) is estimated first. The results, not shown here but available upon request from the authors, indicate that in general there is no statistically significant autocorrelation structure in most of the return. Then, a restricted version of Eq. (6) is estimated excluding the trading volume and using GARCH (1,1) parameterization (*Several GARCH models (p, q) for p = 1, 2 and q = 1, 2, have been estimated. Results from some model selection criteria and log likelihood ratio test show that GARCH (1,1) is an appropriate parameterization for all return series. GARCH-M model has also been estimated. Since the coefficient of standard deviation in the mean equation was not statistically significant in most models, GARCH (1,1) model was used instead. The GARCH (1,1) model suggested by*

Bollerslev (1986) does not consider the possibility of asymmetry in the conditional volatility. However, these are introduced into the model suggested by Glosten et al. (1993), called GJR model. In this model, the equation for conditional variance is: $\sigma_t^2 = \beta_0 + \beta_1\varepsilon_{t-1}^2 + \beta_2\sigma_{t-1}^2 + \beta_3 V_t + \delta D_t \varepsilon_{t-1}^2$*, where* D_t *equals one if* $\varepsilon_{t-1} < 0$ *(innovation in t-1), and zero for the remaining cases. The asymmetrical effect is captured if* $\delta > 0$*, noting that the effect on the volatility changes depending on the sign of the innovation in t-1. This model was applied for each series and results show that there is no significant asymmetry in the conditional volatility*).

The estimated parameters $\hat{\beta}_1$ and $\hat{\beta}_2$ are reported in Table 3. To evaluate the degree of persistence in volatility, we also report $\hat{\beta}_1 + \hat{\beta}_2$. Table 3 also contains Akaike Information Criterion (AIC) to provide the basis for a comparison of the GARCH models with and without trading volume. As shown in the table, all estimated coefficients are statistically significant at one percent level. Results also indicate a high degree of persistence in most stocks' volatility.

Table 3. Results of GARCH (1,1) models

Stocks	α	β	$\alpha+\beta$	AIC
AFYON	0.136* (0.011)	0.818* (0.012)	0.954	-3.888
AKBANK	0.077* (0.008)	0.899* (0.011)	0.976	-3.824
AKGRT	0.096* (0.009)	0.895* (0.009)	0.991	-3.820
AKSUE	0.185* (0.019)	0.755* (0.023)	0.940	-3.934
ARCLK	0.055* (0.005)	0.943* (0.005)	0.998	-3.710
BAGFS	0.129* (0.009)	0.869* (0.007)	0.998	-3.990
BEKO	0.109* (0.010)	0.884* (0.008)	0.993	-3.825
BRISA	0.116* (0.011)	0.864* (0.011)	0.980	-3.934
BUCIM	0.310* (0.021)	0.639* (0.015)	0.949	-4.648
DGZTE	0.117* (0.011)	0.842* (0.013)	0.959	-3.322
DOGHOL	0.086* (0.008)	0.907* (0.007)	0.993	-3.488
ECİLC	0.143* (0.013)	0.836* (0.013)	0.979	-3.731
EGGUB	0.207* (0.021)	0.607* (0.028)	0.814	-3.697
EREGLİ	0.075* (0.007)	0.919* (0.007)	0.994	-3.828
FİNBN	0.102* (0.011)	0.872* (0.013)	0.974	-3.683
FROTO	0.071* (0.006)	0.926* (0.005)	0.997	-3.824
GARANTİ	0.170* (0.026)	0.370* (0.068)	0.540	-3.303
GARGYO	0.259* (0.022)	0.638* (0.024)	0.897	-3.627
KOÇHOL	0.128* (0.013)	0.840* (0.016)	0.968	-3.814
KRDMA	0.219* (0.017)	0.688* (0.014)	0.907	-3.297
MENDRS	0.027* (0.004)	0.968* (0.004)	0.995	-3.896
MMART	0.198* (0.016)	0.741* (0.015)	0.939	-3.533
SAHOL	0.129* (0.014)	0.850* (0.014)	0.979	-3.901
TCELL	0.180* (0.002)	0.759* (0.025)	0.939	-3.829
TUBORG	0.108* (0.007)	0.886* (0.005)	0.994	-3.884

Note: The standard errors are given in parentheses and * indicates significance at 1% level

The unrestricted version of Eq. (6) is also estimated including the trading volume and empirical results are reported in Table 4 (*Balaban (1995) finds significant day-of-the-week effect in the ISE composite index. A model that includes dummies controlling this anomaly and financial crisis of February 2001 has also been estimated. The results indicate that there is in general no significant day-of-the-week effect for the sample individual stock returns. Interestingly, in majority cases, the coefficient of dummy variable that controls financial crash is insignificant. Hence, we rely on a parsimonious specification of Eq. (6). Although the results are not reported, they are available upon request from the authors*.). In 19 out of 25 cases, the coefficients on trading volume are statistically significant at least at five percent level. These results imply a strong correlation between return volatility and trading volume, which is well documented in previous studies. However, the results also show that in the majority of cases, there is a very small reduction in the volatility persistence. Only for six stocks in the sample, namely Afyon, Akbank , Arcelik, Ege Gubre, Eregli, and Garanti Bankası, we can observe a relative decrease in volatility persistence. Hence, including trading volume in the conditional variance equation does not result in a significant reduction of volatility persistence for most sample stocks. As seen in Table 4, the sums of $\hat{\beta}_1$ and $\hat{\beta}_2$ are fairly close to unity, and do not undergo noticeable change when compared to the model without the trading volume variable (*As seen in Table 3 and Table 4, the AIC measures are lower in all cases for the model with trading volume variable.)*. These findings are consistent with findings of a number of studies in emerging markets (*Ahmed, et al (2005) in Malaysia, and Huang and Yang (2001) in Taiwan have found similar results.)* including Salman's findings on volume-return relationship for ISE. Bohl and Henke (2003), and Pyun (2000), however, confirmed that persistence in return volatility tends to disappear when volume is included in conditional variance equation in Polish and Korean stock markets, respectively. Lamoureux and Lastrapes (1990) suggest that after including the proxy for daily information arrivals (trading volume), the ARCH effect vanishes. At least part of the persistence of stock volatility can be explained away by information arrivals. In this respect, compared with the empirical evidence on the return-volume relationship for the developed markets, the findings on Turkish stocks do not fully support the existence of Mixed Distribution Hypothesis (MDH) (Gallo and Pacini, 2000; Omran and McKenzie, 2000) *(These papers, among the others, have found a high degree of volatility persistence for the US and UK stocks.)* There might be several reasons leading to this outcome. First, the pattern of daily information arrivals and the information content of trading volume may be different in the Turkish stock market than those observed in developed markets. Particularly, as witnessed in many emerging markets, majority of stock market participant in Turkey are short-term myopic investors, who frequently engage in speculative activities. Thus, their behavior can be characterized by overreaction to new information and announcements, lacking fundamental analysis. Second, the price limits imposed by ISE (*Until 1994, the change in daily price was limited to 10%, and after 1994, it was increased to 20%)*, may cause volatility to spread over a longer period of time, as suggested by volatility spillover hypothesis (Kyle, 1988). Third**,** the number of transactions rather than the trading volume might be a better proxy to represent daily information arrivals. (see Jones, Kaul and Lipson, 1994).

Table 4. Results of GARCH (1,1) models with trading volume

Stocks	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\delta} \times 10{,}000$	$\hat{\alpha}+\hat{\beta}$	AIC
AFYON	0.227*(0.027)	0.118*(0.028)	2.100* (0.106)	0.345	-3.906
AKBANK	0.157*(0.020)	0.492*(0.034)	1.800* (0.097)	0.649	-3.848
AKGRT	0.101*(0.009)	0.881*(0.011)	0.164* (0.065)	0.982	-3.824
AKSUE	0.250*(0.029)	0.591*(0.027)	0.985* (0.081)	0.841	-3.972
ARCLK	0.289*(0.039)	0.290*(0.051)	2.800* (0.189)	0.579	-3.714
BAGFS	0.197*(0.017)	0.672*(0.014)	0.666* (0.001)	0.869	-4.005
BEKO	0.109*(0.010)	0.884*(0.008)	0.009 (0.037)	0.993	-3.824
BRISA	0.135*(0.013)	0.819*(0.013)	0.258* (0.038)	0.954	-3.947
BUCİM	0.333*(0.025)	0.529*(0.023)	0.520* (0.038)	0.862	-4.686
DGZTE	0.123*(0.012)	0.829*(0.015)	0.103 (0.077)	0.952	-3.321
DOGHOL	0.088*(0.008)	0.901*(0.009)	0.160* (0.055)	0.989	-3.492
ECİLC	0.153*(0.014)	0.826*(0.014)	0.136 (0.045)	0.979	-3.732
EGGUB	0.306*(0.029)	0.366*(0.027)	12.400* (0.090)	0.672	-3.730
EREGLİ	0.233*(0.026)	0.234*(0.041)	4.500* (0.182)	0.467	-3.779
FİNBN	0.103*(0.012)	0.870*(0.013)	0.029 (0.031)	0.973	-3.683
FROTO	0.153*(0.018)	0.724*(0.018)	0.077* (0.000)	0.877	-3.830
GARANTİ	0.101*(0.016)	-0.010(0.054)	7.200* (0.305)	0.091	-3.310
GARGYO	0.059*(0.007)	0.879*(0.012)	0.135* (0.047)	0.938	-3.475
KOÇHOL	0.124*(0.014)	0.845*(0.017)	-0.078 (0.083)	0.969	-3.814
KRDMA	0.436*(0.044)	0.287*(0.039)	2.200* (0.207)	0.723	-3.316
MENDRS	0.028*(0.004)	0.966*(0.004)	-0.036** (0.019)	0.994	-3.896
MMART	0.175*(0.015)	0.770*(0.015)	-0.107** (0.042)	0.945	-3.533
SAHOL	0.135*(0.015)	0.840*(0.016)	0.183* (0.066)	0.975	-3.901
TCELL	0.192*(0.021)	0.739*(0.027)	0.139 (0.111)	0.931	-3.829
TUBORG	0.101*(0.007)	0.888*(0.005)	-0.091* (0.021)	0.989	-3.888

Note: The standard errors are given in parentheses and *and ** indicate significance at 1% and 5% levels, respectively.

CONCLUSION

This paper has analyzed the relationship between trading volume and return volatility for 25 individual stocks in Istanbul Stock Exchange by testing the validity of Mixed Distribution Hypothesis (MDH) when volume is taken as the proxy for the rate of daily information arrivals. The empirical results verify that there is a significant interaction between trading volume and return volatility contemporaneously when volume is integrated into conditional variance equation of returns, supporting empirical findings of seminal studies on emerging markets. Nevertheless, the persistence in return volatility does not diminish after incorporating trading volume for majority of stocks. Thus, these findings provide strong evidence against the validity of MDH in Turkish stock market. These results might be largely attributed to the existence of substantial speculative trading and price limits observed in Turkish stock market.

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Appendix 1: List of Firms Included in the Sample:

Firm	Stock Symbol
AFYON CİMENTO	AFYON
AKBANK	AKBANK
AK SİGORTA	AKGRT
AKSU ENERJİ	AKSUE
ARCELIK	ARCLK
BAGFAS	BAGFS
BEKO ELEKTRONIK	BEKO
BRISA	BRISA
BURSA CIMENTO	BUCİM
DOGAN GAZETE	DGZTE
DOGAN HOLDING	DOGHOL
ECZACI İLAC	ECİLC
EGE GUBRE	EGGUB
EREGLİ DEMIR CELIK	EREGLİ
FİNANS BANK	FİNBN
FORD OTO SANAYII	FROTO
GARANTİ BANKASI	GARANTİ
GARANTI GAYRIMENKUL YATIRIM ORTAKLIGI	GARGYO
KOC HOLDING	KOÇHOL
KARDEMIR A	KRDMA
MENDERES TEKSTIL	MENDRS
MARMARIS MARTI	MMART
SABANCI HOLDING	SAHOL
TURKCELL	TCELL
TUBORG BIRACILIK	TUBORG