Effects of Price Limits on Volatility:
Evidence from the Istanbul Stock Exchange

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ABSTRACT

There has been much discussion among the regulators, investors and academics in policy circles to control the increasing volatility by using the price limits on financial markets. In spite of the strong existence of price limits worldwide, there is no much information regarding the effects of price limits on volatility and price discovery. Most of the previous studies find no evidence for the price limits that reduce the volatility.

This study examines the effects of price limits on volatility in stock returns through testing the overreaction and information hypotheses by using the same methodology in Phylaktis et al. (1999) for Athens Stock Exchange in one of the leading emerging markets - Istanbul Stock Exchange (ISE) in the period between years 1990 and 2001 for a larger sample. More specifically, we investigate the effects of increase in price limits on volatility in ISE in the period following the structural change in July 14, 1994 since daily cumulative price limit is doubled as a result of transition from one to two sessions in a trading day by using the econometric techniques such as serial correlation and GARCH models.

Our results do not support the information hypothesis in contrast to findings of Phylaktis et al. (1999). Serial correlation analysis gives us no strong evidence to reject or confirm the information hypothesis and inconclusive. Therefore, this inconclusive result motivates us to further analysis in future. GARCH estimation on daily and monthly stock returns controlling for structural breaks, financial and economic crises, trading activity and macroeconomic factors point out in a direction that volatility on stock returns has reduced despite the increase in daily price limits in the period following the structural change in ISE on 14 July, 1994. The majority of stock exhibit a *negative* and significant sign for the coefficient on the dummy variable. The results are robust to data frequency, leverage effect, financial crises and macroeconomic indicators.

In other words, with double sessions and despite broader implicit daily price limit ranges, volatility seems to *decline*. Findings imply that transition from one to two sessions in a trading day with lunch-break makes positive impact in reducing the volatility in a environment where the price limit is almost doubled. It seems that the two hour lunch-break between the daily sessions has the effect of a circuit breaker, thus facilitating the dissemination of information and preventing severe overreaction to news events which is consistent to overreaction hypothesis.

Finally, we find that volatility has decreased after the increase in price limits both for cross-section of stocks and overall index as well in ISE and thus price limits have no impact on volatility in stock market by the positive contribution of trading halt in the middle of the trading day.

[#] DRAFT VERSION

The paper could not be completed since our time constraints and so that this is preliminary version of our study. Further analyses will be added to the paper in the following days such as; *investigation of the volatility spillover, delay in price discovery, and trading interference hypotheses and the behavior of stock prices after they hit the limits with using larger sample.*

Keywords: Price limits, volatility, emerging markets, ARCH-GARCH modelling
JEL Classification Code: G10 – G14

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1. Introduction

Increasing volatility in returns of stocks following the crashes in financial markets around the world in last two decades attracted the regulators, investors and academics. There has been much discussion in policy circles to control the volatility by using the price limits on financial markets. Price limits are boundaries established by market regulators to confine daily movements of security prices within a predetermined price range. Daily price limits have two attributes to control volatility: first, they establish price constraints, second, they provide time for rational reassesment during times of panic trading. Supposedly, it prevents freefall of prices, prevent wild swings and provides time-out period to cool-off. Price limits are currently used in the U.S. futures markets and in many exchanges around the world including Italy, Greece, France, Japan, Taiwan, Thailand, Malaysia, Spain, Austria, Belgium, Mexico, Netherlands, Switzerland[1] and Turkey. In spite of the strong existence of price limits worldwide, there is no much information regarding the effects of price limits on volatility and price discovery which has important policy implications for the regulators. In fact, there are very few studies on price limits.

2. Literature Review

Price limits inevitably affect price resolution and the magnitude of such impacts would depend on the level of price limits. The larger the limits, the less distortion there would be on price resolution. Hence the debate on the effects of price limits on volatility and the level of price limits is of great interest to the market participants and policymakers. There are also very few studies on the appropriateness of current levels of price limits in this regard. Therefore, it is in the public interest to evaluate whether current limit levels are too narrow or too high in that they severely hinder the equilibrium price from being reached in the market.

Proponents argue that price limits reduce overreactions, while others suggest that price limits make trading impossible and therefore harm the price discovery process. According to the overreaction hypothesis, the price limits can be used to prevent short-term overreaction. One question is whether price limits result in systematic price movements in the direction of the price limit as predicted by the magnet effect and how prices behave after they hit a limit price.

[1] Roll (1989)

If the direction is reversed on the next day following the locked limit day, then price limits may have a positive effect. If price limits are effective in preventing overreaction, there should be price reversals after limit prices are hit. Therefore, such an effect can be through interday returns between the locked limit day and the day after.

There are almost five different reasons that are used for imposing daily price limits. Overreaction hypothesis is the most popular one among these. Ma, Rao, and Sears (1989a) find evidence of price reversals after limits are reached, indicating overreaction and subsequent correction and also volatility subsides. One of the arguments brought by Telser (1981) is that price limits can give traders time to consult their principles during a big price swing. Second, Brennan (1986) presents a model that price limits can be used to substitute for margin requirements. Third, exchanges use price limits as a bargaining tool with the government which is stated by Miller (1989), Moser (1990), France et al. (1994). Lastly, Kodres and O'Brien (1994) present that price limits may enhance the total welfare by transferring risk between different group of traders in the market.

Many authors have suggested that price limits are likely to generate a "gravitation" or "magnet" effect which states that the price of a security is drawn toward the price limit. Under the magnet effect hypothesis, market participants should have an increasing demand for liquidity on the buyside of the market as prices approach the halt trigger level. For example, Miller (1991) argues that price limits might become self-fulling as traders rush to avoid being locked into their positions when prices become in the range of the trigger point. In contrast, Berkman and Steenbeek (1998) investigated the influence of daily price limits on the price formation process of financial futures on Nikkei-225 futures contracts which are traded both in Osaka Securities Exchange and Singapur International Monetary Exchange (SIMEX) with price limits. They do not find any evidence to support the gravitation effect.

Another question might be the influence of price limits on volume and volatility when price approaches the limits and the degree of damages on liquidity and volatility done by the price limit rule. It is clear that price limits impose liquidity costs on trades for traders who want immediate execution since limits are obstacle for them to do so. Number of locked limit days is important to understand the negative effects of price limits on market rather than large number of limit moves since traders really face liquidity problem in locked market in a stock. Number of limit moves and locked limit days decreases as the price limit levels increase and price limit rule can prevent overreaction while not hurting liquidity too much. Volume and volatility are expected to change according to Subrahmanyam (1994) who examined the exante effects of circuit breakers.

However there are few papers on the effects of trading halts on volatility and volume such as Amihud and Mendelson (1987, 1991), Stoll and Whaley (1990), Gerety and Mulherin (1992), Lee, Ready and Seguin (1994), there is very little empirical evidence for the role of price limits. The main conclusion of the studies on trading halts is that trading halts do not reduce volatility and liquidity in stock market. Both volume and volatility increase right after the trading halt. Regulators argue the advantage of trading halts in the way that halts lessen the breakdown in the transmission of information among the different market participants.

Studies on price limits such as Chung (1991) for the Korean stock market, Chen (1993) for the Taiwan find no evidence for the price limits that reduce the volatility. Kim and Rhee (1997) find similar conclusion that price limits are ineffective. Ma, Rao and Sears (1989) present evidence that price limit rule has been effective in the Treasury bond futures market which help to volatility declines after limit moves. Huang (1997) investigates whether the stock market overreacts following up limit moves and down limit moves to test the overreaction in Taiwan stock market. He found that there are significant price reversals following the limit moves for both up-limit and down-limit cases.

On the other hand, Chen (1998) investigates the overreaction hypothesis and evaluates the effect of price limits on price resolution in future markets. He found little evidence to support the overreaction hypothesis. The direction of price movements on the next day after a big price swing is generally unpredictable so that overreaction is not a good rationale for imposing the price limit rules in futures markets. Chen also provide evidence that the market is relatively efficient in processing information, in general. Phylaktis, Kavussanos and Manalis (1999) have examined the effects of price limits on the volatility in Athens Stock Exchange by testing the information and overreaction hypotheses using the econometric techniques such as serial correlation and GARCH models. Their results show support for the information hypothesis. Thus, price limits only prolong the number of trading days it would take for the market to adapt towards equilibrium. Price limits have no effect on volatility, particularly to reduce it in Greek market.

Recently, Kim and Rhee (1997) examined three hypotheses which are problems with price limits that has been argued by the opponents; volatility spillover, delay in price discovery, and trading interference for the small sample of stocks in Tokyo Stock Exchange. Fama (1989) states that volatility may increase if the price discovery is intervened. This is supported by Kyle (1988) and Kuhn, Kuserk, and Locke (1991). Kuhn et al. (1991) find that limits were ineffective in reducing volatility during the 1989 mini-crash in U.S. Lehmann (1989) also suggests that imbalances in supply and demand in trading induce prices to reach their limits, which implies a transfer of transactions to subsequent days. Therefore, price limits may cause volatility to spread out over a longer period of time because limits prevent large one-day price changes and immediate price corrections. This spillover to subsequent trading days is consistent with the volatility spillover hypothesis. Lee, Ready, and Seguin (1994) supports the hypothesis by finding that volatility and volume increase on days following trading halts.

The delay in price discovery is another costly problem induced by price limits. Trading usually stops when the price hit the limits until the limits are recalculated. Price boundaries may prevent stocks reaching their equilibrium prices for that day. If limits block prices, then stocks have to wait until a subsequent trading period to continue toward their true price which is consistent with the delayed price discovery hypothesis.

Lastly, stocks become less liquid if price limits prevent trading, hence trading activity on following days may increase as a result of interference. This problem is also noted by Fama (1989) and Lauterbach and Ben-Zion (1993) who indicated that interference in liquidity is a cost of circuit breakers. Alternatively, Lehmann (1989) argues that blocking the trading induce prices to reach their limits and impatient investors will trade at unfavorable prices or patient investors will wait for prices to reach the equilibrium. In either situation, the trading volume will be higher on the days following limit-days which is consistent with the trading interference hypothesis. Overall, evidence of Kim and Rhee (1997) supports all three hypotheses suggesting that price limits may be ineffective.

Lehmann (1989) and Miller (1989) both suspected the information gained from examining volatility after limit days since we can not know what would have happened in the absence of price limits. This should also be considered in empirical analysis to measure the effects of limits on volatility. Therefore, most studies have used an event-study methodology where they examine liquidity and volatility before and after a price limit-hit.[2] These studies, while potentially beneficial, are subject to problems of interpretation because of serial dependence of returns.[3] Kim and Limpaphayom (2000) take different approach to identifying price limit effects. They attempted to identify the characteristics of stocks that frequently hit price-limits. and found that those stocks typically have the same characteristics; volatile, heavily traded and small market caps.

Within this framework, this study examines two testable hypotheses presented here for the effects of price limits on volatility in stock returns; information hypothesis and overreaction hypothesis.

According to information hypothesis, if a price limit exists and true equilibrium price falls outside the daily price limits, the price will continue to move in a direction towards equilibrium as new trading limits are imposed. Price limits only prolong the number of trading days it will take for the market to adapt to a disturbance towards equilibrium. Thus, there should be longer and more significant serial correlation of stock returns and volatility should not change. Therefore, two hypotheses to test for the information hypothesis are;

H1: More significant serial correlations in returns in post-limit period.

H2: There should be no difference in volatility between pre- and post-limit periods.

Overreaction hypothesis explained above requires that investors overreact to new information and cause prices reach to the limits. Triggered price limits give additional chance to market to evaluate the information and to reposition their strategies. Finally, this cool-off period decreases the volatility. Thus, testable hypothesis is;

H3: Volatility in post-limit period should be less than in pre-limit period.

This study examines the effects of price limits on volatility in stock returns through testing the overreaction and information hypotheses by using the same methodology in Phylaktis et al. (1999) in one of the leading emerging markets - Istanbul Stock Exchange (ISE) in the period between years 1990 and 2001. To our knowledge, this is the first study that investigates the effects of price limits on stock returns in ISE. Main motivation here in this study is a structural change made by the ISE in July 14, 1994, which increased the theoretical level of

[2] Chen (1998), Ma et al. (1989a, b), Kim and Rhee (1997)

[3] Chen (1998), Lehmann (1989), Miller (1989), France et al. (1994)

daily price limits to 21 % from 10 % by dividing the trading day into two separate sessions and imposing 10 % price limits to each of the sessions. There was only one two-hour long session with a 10 % limit in pre-change period whereas there are now two different 2½ hour-long sessions in which the price limit is 10 % for each of them in post-change period. Thus, we investigate the effects of increase in price limits on volatility and more specifically whether there is an increase in volatility of daily stock returns in ISE in the period following the structural change in July 14, 1994 since daily cumulative price limits raised to 21 % (compounded of ten percent) from 10 %.

The remainder of the paper is organized as follows: Section 3 describes a brief description of institutional specifications of ISE, data and empirical methodology used in this study. Next section, Section 4 presents the empirical tests and results. The last section, Section 5, contains the summarized results and concluding remarks of the study.

3. Empirical Research

3.1 Institutional Specifications of the ISE

Although the Istanbul Stock Exchange (ISE) was established in 1986, it has achieved rapid development. As a leading emerging market, ISE's progressive infrastructure and dynamism are attracting increasing international interest. In average, foreign and international institutional investors own 50% of the free float of the shares at the ISE. Total market capitalization is approximately US$ 80 Billion whereas it is a highly active market with an average daily trading value of US$ 753 Million and 315 listed stocks at yearend of 2000.

The ISE is an order-driven, multiple-price, continuos auction market with no market makers or specialists. The trading is realized through the computerized trading system. There is no opening session or pre-open procedure at the ISE. The market is open Monday through Friday, (morning session) from 09:30 a.m. until 12:00 and after two hours lunch break, (afternoon session) from 2:00 p.m. to 4:30 p.m. Price limit is 10% for each session in a day and the limits are calculated based on the weighted average prices of previous session. The "National-100 Index" (ISE-100) which is the main market indicator of the Istanbul Stock Exchange is a market capitalization-weighted index and represents at least 75% of the total market capitalization, traded value, number of shares traded and number of trades realized in the market.

3.2 Econometric Methodology

In order to examine the hypotheses that were mentioned above, various tests were performed. First, we look at the serial correlation properties of the daily returns, then we estimate the time varying variance of daily and monthly stock returns, thus examining the impact of the transition the Istanbul Stock Exchange underwent on July 14, 1994.

3.2.1 Serial Correlation Analysis

In order to examine the plausibility of the information hypothesis, we estimate the serial correlations of the daily returns in the period before and after the structural change. Positive serial correlations in the first regime followed by lower serial correlations in the second regime imply the confirmation of the information hypothesis. Thus we estimate the autoregression below and use the Chow breakpoint test to verify the existence of a significant structural change:

(1) $r_t = \sum_{i=1}^{N} f_i r_{t-i} + e_t$

(2) $e_t \sim NID(0, s^2)$

3.2.2 GARCH Analysis

Modeling the time varying variance of the stock returns allows us to examine the implications of the hypotheses that concern the volatility before and after the structural change. High frequency stock returns, as well as other financial assets, exhibit periods of large absolute changes followed by periods of relatively small absolute changes. This phenomenon is known in the literature as "clustering." Also, after careful examination of the descriptive statistics, one immediately notices the high level of kurtosis prevalent in the stock returns. The most successful and thus common method that allows one to model the time varying volatility and leptokurtosis in stock returns has been the generalized autoregressive conditional heteroskedasticity (GARCH) models. GARCH models allow persistence in the volatility process by imposing an autoregressice structure on the conditional variances.

The core GARCH model we use to analyse the daily stock returns in the ISE is as follows:

$$(3)\quad r_t = \sum_{i=1}^{N} f_i r_{t-i} + e_t$$

$$(4)\quad e_t \sim NID(0, s_t^{\,2})$$

$$(5)\quad s_t^{\,2} = a_0 + \sum_{i=1}^{p} a_i e_{t-i}^2 + \sum_{j=1}^{q} b_j s_{t-j}^2$$

where α_i and β_j are both greater than or equal to zero for i=0,…,p and j=1,…,q, so that σ_t^2 is greater than zero. The sum of the GARCH coefficients, i.e. α_i and β_i denote how persistent the conditional variance is to a shock to the system. One interpretation of such a shock is the arrival of news. For the variance to be stationary, this sum should be less than unity. For pure ARCH models, $\beta_j=0$ for all j=1,…,q[4].

However, our analysis as well as previous work indicate that trading activity, represented by volume or the daily value of transactions, may be an important determinant of conditional volatility in the stock returns we consider. Trading activity proxies for the amount of information flow into the market, which has been given as one of the explanations for the prominence of GARCH models[5]. The relationship between the volatility of returns and trading volumes is theoretically based on the implication of the Mixture of Distributions Hypothesis, where the variance of daily price increments is heteroskedastic, especially when related to the rate of daily information arrival.[6]

[4] For a review of ARCH modeling in finance see Bollerslev, Chou and Kroner (1992) and/or Bollerslev, Engle and Nelson (1994) for a more comprehensive treatment.
[5] Phylaktis, Kavussanos and Manalis find that trading activity is important for the Athens Stock Exchange (1996, 1999). See Berry and Howe (1994) for an example of news releases and trading volume and again Bollerslev *et al*. (1992) for the relationship between GARCH models and news releases.
[6] Again refer to Phylaktis *et al*. (1999).

Thus, the conditional volatility represented by equation (6) is modified to include the lag of the value of daily transactions[7]:

$$(6)\quad s_t^2 = a_0 + \sum_{i=1}^{p} a_i e_{t-i}^2 + \sum_{j=1}^{q} b_j s_{t-j}^2 + nV_{t-1}$$

where V_t represents the trading volume series.

In order to test the effects of the structural break the Istanbul Stock Exchange underwent, we further augment the variance equation in our framework to include a dummy variable that will pick up the effects of regime changes on volatility. The dummy variable takes the values of zero before July 14, 1994 and unity thereafter. Thus our variance equation is modified further and takes the form:

$$(7)\quad s_t^2 = a_0 + \sum_{i=1}^{p} a_i e_{t-i}^2 + \sum_{j=1}^{q} b_j s_{t-j}^2 + nV_{t-1} + dD_t$$

where D_t is the dummy variable associated with the structural break.

Finally, dating all the way back to Black (1976), the impact of the type of news seems to have asymmetric affects on volatility. Following Glosten, Jaganathan and Runkle (1993) and Zakaian (1990), we model that bad news has a greater impact on stock volatility than good news for various stocks, this is known as a threshold ARCH, or TARCH specification. Thus we finally augment the variance equation in our GARCH model as follows:

$$(8)\quad s_t^2 = a_0 + \sum_{i=1}^{p} a_i e_{t-i}^2 + \sum_{j=1}^{q} b_j s_{t-j}^2 + nV_{t-1} + dD_t + te_{t-1}^2 I_{t-1}$$

where I_t takes the value of unity if the news is bad, and zero if the news is good. For exposition, let p=q=1. Hence, good news has the impact on volatility of α, while bad news has an affect of $(\alpha + \tau)$. If τ is greater than zero, leverage effects exist, and thus the impact of news on volatility is asymmetric.[8]

[7] Trading volume is important only for a limited number of stocks. The lag of volume is used t avoid simultaneity issues, see Harvey (1989) for further details.
[8] Quasi-likelihood robust standard errors were used, for the reason that most of the residual that displayed significant leverage effects had residuals that were highly leptokurtic.

3.3 Data description

The data set is comprised of daily closing prices of 30 stocks traded on the ISE and the general stock index, along with their respective transaction series from the January 2, 1990 to June 7, 2001, totaling 2606 observations. The data set is collected from the ISE records and are adjusted for stock splits and dividend payments. We also used monthly data. The stocks that have been selected have reached their respective price limits before the structural break, July 14, 1994. They encompass heavily and lightly traded stocks, relatively high and low market capitalization and cover a very broad variety of sectors. Information on these stocks are summarized in Table 1.

The daily stock returns are calculated as the logarithmic first differences of the stock prices, and the general market index.[9] To assess the distributional properties of the stock returns and more importantly the importance of nonlinearity, various descriptive statistics are summarized in Table 2. All stock returns are significantly leptokurtic with respect to the normal distribution. The Ljung-Box (1978) Q(20) statistic shows evidence of serial correlation for the return series, and the $Q^2(20)$ statistics gives evidence in favor of conditional heteroskedasticity.[10] This along with the extreme kurtosis in the return series suggests the use of GARCH models, where the temporal dependence of volatility can be modeled.

4. Empirical Findings

4.1 Serial Correlations

To test the information hypothesis, Table 3 provides the serial correlations from the single session and double session regimes. For the information hypothesis not to be rejected, serial correlations in the single session period that exhibited serial correlation should exhibit lesser degrees of persistence displaying lower magnitudes, i.e. lower positive values or negatives serial correlations in the second regime. This is because in a single session price limitations restrict movements to a ten percent bound. Thus if the new equilibrium value lies beyond the

[9] All stock returns exhibit mean reversion, and preliminary analysis supports this statement, where the null hypothesis of a unit root is rejected for a return series.
[10] The null hypothesis of conditional homoskedasticity implies that $Q^2(k)$ will be distributed asymptotically $\chi^2(k)$.

ten percent limit, it will take several days until the series settles at its new equilibrium. In the two session case, the bounds are in absolute value approximately equal to 21 percent, the price limit restraint is therefore not as binding.

For five stocks depicted in Table 4, serial correlations were positive in the first regime, whereas in the second regime the magnitudes all decreased. However, the only way to see if indeed this finding is robust we have to test for a structural shift. Since we know the date a priori, the most appropriate test is the Chow breakpoint test at date July 14, 1994. We thus estimate equation (1), using 10 and 30 lags. The results are depicted in Table 4. As can be seen only two of the five stocks support the information hypothesis that price limits delay the adjustment process. Support in favor of the information hypothesis is mixed using this technique. Results from simple serial correlations and Chow test are inconclusive which motivates us to further anaysis, for example using information regarding limit-hits.

4.2 GARCH estimation on daily stock returns

We modeled the stock returns and their time dependent variances using GARCH models, the results which are shown in Table 5. The appropriate GARCH model is selected by taking into consideration various selection criteria, the most important are the sum of squared residuals, the Akaike and Schwarz information criteria (AIC and SIC respectively) and the properties of the residuals. The log likelihood function is maximized using the Bernt-Hall-Hall-Hausman iterative algorithm. In most cases the GARCH(1,1) or GARCH(1,2) models are employed although there are series that are modeled using richer dynamics.

All autoregressions utilized are statistically significant, in that past returns have explanatory power for current stock returns. The significance of the autocorrelations is typically the result of the price adjustment delays such as the lag between transaction price adjustment and quotation price adjustment, as well as transaction prices propagating randomly between bid and ask prices. This is evidence that the mean return reveals weak informational inefficiency as past returns contain valuable information for predicting future returns.[11]

Hence the characterization of stock returns containing GARCH effects is appropriate. The conditional variance in most cases is fairly persistent, this is because the sum of the GARCH coefficients α_i's and β_j's is typically close to one. The improvement in the Ljung-Box (1978) portmanteau statistics for the standardized residual compared with those of the raw series indicate that the GARCH models utilized successfully capture the time varying volatility.[12] For certain series, residuals display significant leptokurticity, we thus use the techniques in Bollerslev-Wooldrigde (1992) to take the non-normality of residuals into consideration.[13]

As can be inferred from Table 5, volume does not factor into the explanation of volatility for many series. However if present, the absence of the volume instrument poses misspecification. Trading activity has no clear and significant impact on volatility. The most important conclusion is that for the majority of stocks, the coefficient on the dummy variable is *negative* and this is typically a significant parameter. In other words, with double sessions and despite broader implicit daily price limit ranges, volatility seems to *decline*. Basic standard deviations of daily returns for the pre-change and post-change periods also confirm this result. It seems the two hour interval between the daily sessions has the effect of a circuit breaker, thus facilitating the dissemination of information and preventing severe overreaction to news events. Leverage effects are also not very important, but when omitted cause implausible point estimates. This result will be elaborated on below.

4.3 GARCH estimation on montly stock returns

The exercises above are repeated, but this time using monthly data. As in many studies, GARCH processes converge to normality due to temporal aggregation, thus the monthly series that depict GARCH effects is less than the original 30. From Table 6, it can be seen that volume and leverage effects have been omitted due to their lack of explanatory power. Also, it seems that the classic ARCH(1*)* model does a fairly good job modeling the monthly series. Persistence in the conditional volatility has decreased. Again the point to emphasize here is that the majority of stock exhibit a *negative* and significant sign for the coefficient on the dummy variable. Evidence that volatility has *decreased* in the second regime is thus *robust* to data frequency. Again supporting the idea that pause in trading between the two daily sessions acts as a daily circuit breaker.

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[11] See Conrad, Kaul and Nimalendran (1991) and Phylaktis *et al*. (1999) for further details.
[12] Ljung-Bow statistics can be obtained from authors by request.
[13] Estimated standardized residual are the residuals divided by the square root of the conditional variance.

Evidence from the past shows that volatility of monthly returns may be influenced by various other variables. Schwert (1989) suggests an array of macroeconomic variables ranging from the inflation to industrial production variability may affect stock market volatility. The intuition being that future macroeconomic uncertainty would affect stock return volatility by influencing future expected cash flows. Furthermore, the decade under analysis has been a decade of economic disaster for Turkey. The stock exchange was faced with several severe domestic and foreign crises as well as natural disasters. The Gulf War in 1990, devaluations in 1994 and 2001, the international financial crises in 1997 and 1998, the 1999 earthquake and finally the banking credit crunch in late 2000 all negatively affected the economic environment. In order to avoid misspecification when modeling the conditional variance, which will bias results, we include appropriate variables to instrument for the macroeconomic circumstances. We add the volatility of inflation and industrial production by estimating an autoregressive system with 12 lags (with seasonal dummies), then re-estimating the same equation using the absolute value of the residuals from the first regression. The fitted values from the second equation are the conditional variances for the variable in the equation.

We also include dummies for the various crises periods, thus the equation for the conditional variance we re-estimate using the additional macroeconomic variables is as follows:

$$(9)\; s_t^{2} = a_0 + \sum_{i=1}^{p} a_i e_{t-i}^{2} + \sum_{j=1}^{q} b_j s_{t-j}^{2} + d D_t + g C_t + \sum_{k=1}^{K} x_k X_{k,t}$$

where the C_t is the respective crisis dummy and X_t is the macroeconomic volatility proxy.

However, augmentation of equation (7) does not lead to any profound changes what so ever, this came as quite a surprise! This finding is however consistent with previous work[14]. Many permutations were tested, combinations of dummies added along with interaction affects, but to no avail. Leverage components were added, for the reason that a dummy for bad news in general may capture interesting dynamics in the volatility process. Once again nothing interesting was uncovered. We attribute this finding to the fact that over a month, excess volatility tends to dissipate, which is verified by the fact that most of the monthly series do not exhibit GARCH effects profoundly as the daily series.

5. Summary and Conclusion

This study examines the effects of price limits on volatility in stock returns through testing the overreaction and information hypotheses by using the same methodology in Phylaktis et al. (1999) in one of the leading emerging markets - Istanbul Stock Exchange (ISE) in the period between years 1990 and 2001 for a larger sample. More specifically, we investigate the effects of increase in price limits on volatility in ISE in the period following the structural change in July 14, 1994 since daily cumulative price limit is doubled as a result of transition from one to two sessions in a trading day by using the econometric techniques such as serial correlation and GARCH models.

Our results do not support the information hypothesis in contrast to findings of Phylaktis et al. (1999) for Athens Stock Exchange. Serial correlation analysis gives us no strong evidence to reject or confirm the information hypothesis and inconclusive. Therefore, this inconclusive result motivates us to further analysis in future. GARCH estimation on daily and monthly stock returns controlling for structural breaks, financial and economic crises, trading activity and macroeconomic factors point out in a direction that volatility on stock returns has reduced despite the increase in daily price limits in the period following the structural change in ISE on 14 July, 1994. The majority of stock exhibit a *negative* and significant sign for the coefficient on the dummy variable. The results are robust to data frequency, leverage effect, financial crises and macroeconomic indicators.

In other words, with double sessions and despite broader implicit daily price limit ranges, volatility seems to *decline.* Findings imply that transition from one to two sessions in a trading day with lunch-break makes positive impact in reducing the volatility in a environment where the price limit is almost doubled. It seems that the two hour lunch-break between the daily sessions has the effect of a circuit breaker, thus facilitating the dissemination of information and preventing severe overreaction to news events which is consistent to overreaction hypothesis.

Finally, we find that volatility has decreased after the increase in price limits both for cross-section of stocks and overall index as well in ISE and thus price limits have no impact on volatility in stock market through the positive contribution of trading halt in the middle of the trading day.

[14] See Phylaktis *et al*. (1999).

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Table and Figures

Table 1
Information on individual stocks.

Stock	Abbreviation	Sector	Average Market Capitalization (in thousands TL as of 1994)
	ADANA	Cement	1,401,038,080
	AFYON	Cement	469,687,500
	AKALT	Textile	1,881,490,275
	AKBNK	Financial	42,386,408,730
	ARCLK	Metal, Machinery	21,561,698,413
	BAGFS	Chemical	1,358,769,841
	DENCM	Construction	496,699,603
	DEVA	Chemical	450,221,111
	DISBA	Financial	1,680,337,302
	EGGUB	Chemical	338,973,214
	ENKA	Financial	1,622,892,857
	EREGL	Steel and Iron	15,645,828,571
	FENIS	Basic Metals	315,362,952
	GARAN	Financial	25,423,809,524
	GENTS	Wood Products	342,519,873
	HEKTS	Chemical	327,631,746
	INTEM	Construction	214,865,357
	ISCTR	Financial	15,025,314,286
	IZOCM	Construction	1,564,861,111
	KCHOL	Financial	42,466,269,841
	KLBMO	Wood Products	318,740,079
	KONYA	Cement	1,503,115,079
	MIGRS	Retail	7,113,888,889
	MRDIN	Cement	1,242,476,190
	MRSHL	Chemical	1,575,368,476
	PETKM	Chemical-Petroleum	22,464,285,714
	THYAO	Transportation	28,992,162,698
	USAK	Construction	344,443,452
	VESTL	Electronics	1,349,637,447
	YKBNK	Financial	7,614,375,000
	ISE		617,685,799,745

Source: ISE Database

Table 2

Summary statistics of daily stock returns

Stock	mean	max	min	stdev	skew	kurt	Jarque-Bera statistic	JB p-value	Q(20)	$Q^2(20)$
ADANA	0.002315	0.55	-0.2022	0.041555	1.103627	16.22089	18610.19	0		
AFYON	0.002032	0.2336	-0.1967	0.05173	0.258881	4.724368	335.7678	0		
AKALT	0.001921	0.1851	-0.2103	0.044397	0.137848	4.560545	260.1297	0		
AKBNK	0.001691	0.1924	-0.6931	0.045416	-1.223448	26.21575	56448.61	0		
ARCLK	0.002147	0.2103	-0.4187	0.044292	-0.54064	10.17159	5448.577	0		
BAGFS	0.001781	0.3185	-0.1957	0.046685	0.240281	5.007578	441.4004	0		
DENCM	0.00253	0.2136	-0.1911	0.051317	0.246908	3.767116	86.21455	0		
DEVA	0.000871	0.1991	-1.16	0.054063	-3.798399	88.33271	760237.7	0		
DISBA	0.001551	0.2048	-0.6931	0.052797	-1.640019	25.66015	54302.65	0		
EGGUB	0.002182	0.237	-0.1982	0.049532	0.244144	4.531387	267.6149	0		
ENKA	0.003411	0.2122	-0.3365	0.050726	-0.029989	4.872488	363.5578	0		
EREGL	0.002021	0.1843	-0.2054	0.044925	0.164616	4.125154	142.3614	0		
FENIS	0.001918	0.2187	-0.2144	0.041969	0.280822	7.304393	1951.846	0		
GARAN	0.002684	0.2522	-0.1854	0.046437	0.183147	4.59186	276.3801	0		
GENIS	0.002526	0.2007	-1.0986	0.051353	-3.902255	87.70434	749501.6	0		
HEKTS	0.001909	0.2069	-0.3293	0.04827	0.131857	5.156132	488.7526	0		
INTEM	0.002289	0.28	-0.1823	0.050577	0.345291	4.219999	203.5723	0		
ISCTR	0.002618	0.214305	-0.678033	0.050649	-0.878197	17.95194	23476.68	0		
IZOCM	0.001656	0.1744	-0.4253	0.043588	-0.463171	9.195234	4064.51	0		
KCHOL	0.001861	0.1728	-0.6931	0.046	-1.223672	24.80263	49859.23	0		
KLBMO	0.001718	0.2231	-0.5188	0.049617	-0.18656	9.009536	3755.284	0		
KONYA	0.002	0.2094	-0.6931	0.046594	-1.000139	24.58948	48695.21	0		
MIGRS	0.003774	0.1951	-0.2007	0.040192	0.313103	5.525964	701.5313	0		
MRDIN	0.002381	0.7027	-0.8329	0.048375	-1.686993	65.78074	409444.7	0		
MRSHL	0.002701	0.2016	-0.1798	0.045656	0.192698	4.592601	278.1119	0		
PETKM	0.002427	0.2007	-0.1823	0.051328	0.272353	3.813032	99.20425	0		
THYAO	0.002142	0.4212	-1.0647	0.059564	-1.969035	45.15022	185636.8	0		
USAK	0.001035	0.2094	-2.3702	0.071369	-14.63852	491.8765	24845231	0		
VESTL	0.000666	0.2231	-3.5553	0.087795	-26.68258	1083.942	121000000	0		
YKBNK	0.002279	0.1963	-0.7372	0.050887	-1.29945	22.93498	41863.99	0		
ISE	0.002745	0.1945	-0.1493	0.032191	0.199478	5.516408	735.1595	0		

Table 3
Serial Correlations of daily stock returns.

		lag 1	lag 2	lag 3	lag 4	lag 5	lag 10
adana	pre	0.077	-0.112	-0.081	0.043	0.037	0.013
	post	0.015	0.068	0.008	0.031	-0.014	0.002
afyon	pre	0.268	0.099	-0.009	-0.019	-0.048	-0.008
	post	0.053	-0.009	-0.059	-0.009	-0.015	0.002
akalt	pre	0.009	0.036	0.004	0.016	-0.005	0.014
	post	-0.023	0.042	0.013	0.053	-0.002	0.03
akbnk	pre	-0.034	0.009	-0.028	-0.005	-0.01	-0.019
	post	-0.022	0.048	-0.014	-0.03	-0.073	0.017
arclk	pre	0.155	0.024	-0.002	0.012	0.038	0.036
	post	0.049	0.038	-0.006	0.007	-0.038	0.035
bagfs	pre	0.087	-0.028	-0.025	0.007	0.054	0.084
	post	0.006	0.029	-0.021	0.003	-0.039	0.037
dencm	pre	0.076	0.006	-0.02	0.039	-0.007	0.073
	post	0.01	-0.022	0.037	0.039	-0.006	0.049
deva	pre	0.115	-0.019	0.017	0.025	0.024	-0.014
	post	-0.004	0.013	0.008	0.023	-0.038	0.016
disba	pre	0.126	-0.022	0.021	0.008	-0.032	0.046
	post	-0.013	-0.013	0.04	0.091	-0.059	0.021
eggub	pre	0.061	0.009	0.02	0.015	-0.035	0.061
	post	0.058	0.015	0.001	-0.013	-0.049	0.025
enka	pre	0.082	0.02	0.022	0.015	0.002	-0.003
	post	0.027	-0.02	-0.017	0.011	-0.049	0.033
eregl	pre	0.191	0.023	0.039	0.049	0.071	0.043
	post	-0.022	0.031	-0.011	0.032	-0.05	-0.007
fenis	pre	-0.04	-0.044	0.071	0.092	0.112	-0.136
	post	-0.012	0.006	-0.028	0.026	-0.01	0.012
garan	pre	0.05	-0.002	0.019	0.065	-0.015	0.035
	post	0.033	0.025	-0.018	0.031	-0.095	0.045
genis	pre	0.082	0.019	-0.033	0.025	0.009	0.056
	post	-0.052	0.011	0.037	0.046	-0.058	0.021
hekts	pre	0.031	-0.031	-0.005	0.033	0.023	0.026
	post	0.008	0.034	0.012	0.05	-0.013	0.039
intem	pre	0.123	-0.02	-0.004	0.035	-0.007	0.047
	post	0.028	0.036	0.045	-0.015	-0.035	0.064
isctr	pre	0.177	0.168	0.051	0.028	0.005	0.009
	post	0.006	0.036	-0.004	0	-0.013	0.048

izocm	pre	0.089	-0.012	-0.01	0.044	-0.001	-0.002
	post	-0.044	0.028	-0.02	0.026	-0.005	0.025
kchol	pre	0.185	0.029	0.033	0.016	0.014	0.022
	post	0.002	0.069	0.007	0.012	-0.074	0.018
klbmo	pre	0.077	-0.06	-0.012	-0.027	-0.009	0.067
	post	-0.063	0.011	0.046	0.044	-0.041	0.072
konya	pre	0.057	0.014	0.003	0.057	0.005	0.074
	post	0.027	0.034	-0.005	0.041	-0.004	0.001
migrs	pre	0.062	0.028	-0.053	0.012	-0.006	-0.001
	post	0.018	0.04	-0.04	-0.01	-0.042	0.02
mrdin	pre	0.136	-0.01	0.055	0.034	0.016	0.044
	post	-0.042	0.065	-0.005	0.019	-0.011	-0.001
mrshl	pre	0.097	0.003	-0.112	-0.019	0.021	0.078
	post	-0.036	-0.031	0.025	0.004	-0.058	0.032
petkm	pre	0.087	0.045	-0.018	0.087	0.028	0.019
	post	0.039	0.08	0.036	-0.01	-0.061	0.044
thyao	pre	0.089	0.043	-0.035	0.015	0.004	0.054
	post	0.032	0.029	0.012	0.007	-0.051	-0.003
usak	pre	-0.019	-0.005	-0.041	-0.025	-0.013	0.015
	post	0.043	-0.005	-0.013	0.022	-0.006	0.024
vestl	pre	0.028	0.007	-0.008	0.01	-0.005	0.006
	post	0.052	-0.011	-0.02	0.011	-0.048	0.019
ykbnk	pre	0.205	0.037	0.007	0.034	0.034	0.014
	post	0.052	0.014	-0.034	0.025	-0.083	0.012
ise	pre	0.244	-0.024	-0.015	0.033	0.03	0.068
	post	0.035	0.033	0.01	0.032	-0.063	0.035

Source: ISE Database

Table 4
Structural stability tests on autocorrelations.

	Nth order autocorrelation	Chow statistic	Significance level
enka	10	0.99	0.45
	30	0.997	0.47
konya	10	0.934	0.51
	30	0.744	0.85
eregl	10	3.96	0
	30	2.1	0
kchol	10	1.26	0.24
	30	1.09	0.34
ykbnk	10	1.78	0.052
	30	1.39	0.07

Table 5
GARCH estimates of daily stock returns

	ADANA	AFYON	AKALT	AKBNK	ARCLK	BAGFS	DENCM	DEVA
ϕ_0 x 10^3	0.000786	0.000786	0.0017	0.0011	0.0016	0.0021	0.0019	0.00061
	0.892	0.892	2.29	1.49	2.21	2.45	1.96	0.68
ϕ_1	0.034	0.034	-0.016	-0.041	0.039			0.03
	1.398	1.4	-0.74	-1.86	1.88			1.357
ϕ_2								-0.045
								-3.11
ϕ_3	-0.047	-0.047					0.032	
	-2.217	-2.22					1.56	
ϕ_4			0.024				0.038	
			1.14				1.84	
ϕ_5	-0.038	-0.08						
	-1.99	-1.99						
ϕ_6					-0.03	-0.052		
					-1.63	-2.54		
α_0	0.00099	0.00099	0.00019	0.0002	0.0001	-0.00016	0.00023	0.000075
	6.744	6.744	5.8	8.94	5.53	-2.062	5.28	4.197
α_1	0.265	0.265	0.15	0.204	0.18	0.15	0.104	0.118
	8.869	8.87	9.24	11.94	7.53	10.97	7.18	5.56
α_2	-0.155	-0.155						-0.054
	-5.319	-5.32						-2.48
β_1	0.805174	0.81	0.77	0.7	0.48	0.74	0.81	0.91
	36.032	36.03	31.36	37.16	3.23	34.03	36.34	76.3
β_2					0.28			
					2.18			
β_3								
τ							0.033	
							1.71	
ν x 10^8	-0.000039	-0.000039				0.00002		
	-6.622	-6.62				4.78		
δ x 10^5	0.000104	0.000104	-0.000017	0.000085	0.000055	-0.000088	-0.000062	-0.000009
	6.516	6.52	-0.95	5.43	3.48	-3.21	-2.58	-0.921
log likelihood	4138.47	4138.5	4637.2	4689.7	4720.6	4496399	4241.49	4363.9
m_3	0.176	0.18	0.22	0.24	0.15	0.31	0.25	0.11
m_4	5.21	5.21	4.08	5.28	4.16	4.76	4.1	4.34
$Q(20)$	37.43	37.43	21.45	26.9	29.84	29.41	23.68	26.4
$Q^2(20)$	25.2	25.2	14	26.5	25.81	19.01	11.7	21

Table 5 (continued)
GARCH estimates of daily stock returns

	DISBA	EGGUB	ENKA	EREGL	FENIS	GARAN	GENIS	HEKTS
ϕ_0 x 10^3	0.002	0.0019	0.0025	0.00099	0.0018	0.0035	0.0021	0.0016
	2.31	2.29	2.7	1.28	4.17	4.93	2.54	1.89
ϕ_1			0.032	0.042	-0.037			
			1.46	1.96	-1.68			
ϕ_2								
ϕ_3	0.031							
	1.63							
ϕ_4	0.043			0.039	0.033	0.074		0.03
	2.21			1.94	1.41	6.34		1.55
ϕ_5	-0.035					-0.063	-0.031	
	-2.13					-5.21	-1.67	
ϕ_6		-0.025						
		-1.26						
α_0	0.000093	-0.000089	0.00042	0.0002	0.00001	0.0014	0.00013	0.000053
	2.41	-0.81	6.28	6.67	8.87	11.87	5.16	4.2
α_1	0.19	0.157	0.2	0.17	0.135	0.076	0.115	0.22
	6.72	8.59	8	9.47	9.52	12.1	9.62	9.02
α_2	-0.12					-0.048		-0.13
	-4.12					-529000		-6
β_1	0.9	0.77	0.5	0.734	0.57	0.393	0.84	0.91
	88.48	37.18	3.87	28.6	5.58	8.72	52.92	92.48
β_2			0.4		0.24			
			1.34					
β_3								
τ		-0.053			0.065			-0.023
		-2.75			2.86			-2.07
ν x 10^8	0.000001	0.000023						
	0.252	3.5						
δ x 10^5	-0.000043	-0.00024	-0.000005	0.000015	0.000104	-0.00059	-0.00005	-0.000014
	-2.56	-4.5		0.86	9.138		-2.47	-1.66
log likelihood	4353.5	4401.1	4299.3	4593.8	5222	4290.8	4561	4495.4
m_3	0.2	0.28	0.1	0.24	-0.012	0.09	0.018	0.21
m_4	4.56	4.72	4.01	4.31	12.86	5.21	3.9	4.47
Q(20)	18.66	17.9	11.83	22.25	15.5	27.8	20.47	17.82
$Q^2(20)$	14.67	18.42	27.1	14.3	6.77	399.5	20.9	19.1

Table 5 (continued)
GARCH estimates of daily stock returns

	INTEM	ISCTR	IZOCM	KCHOL	KLBMO	KONYA	MIGRS	MRDIN
ϕ_0 x 10^3		0.0021	0.0019	0.001	0.0019	0.00094	0.0031	0.00231
		2.33	2.53	1.43	2.1	1.2	4.39	2.95
ϕ_1	0.052		-0.038					0.017
	2.57		-1.82					0.8
ϕ_2		0.034		0.043	-0.028			
		1.57		2.27	-1.46			
ϕ_3	0.031		-0.032				-0.038	
	1.51		-1.62					
ϕ_4					0.0072	0.03		0.007
					0.35	1.46		0.4
ϕ_5								
ϕ_6	-0.034							
	-1.69							
α_0	0.0002	0.0002	0.00016	0.000077	0.00013	0.00018	0.0001	0.0031
	6.23	4.77	6.4	4.82	4.64	5.89	5.89	136
α_1	0.16	0.141	0.14	0.122	0.084	0.19	0.13	0.14
	10.5	8.83	9.58	9.33	4.64	7.23	11.33	6.7
α_2						-0.056		0.13
								6.68
β_1	0.78	0.75	0.78	0.84	0.49	0.786	0.82	
	38.21	26.76	38.31	49.72	2.64	32.34	58.12	
β_2					0.372			
					2.12			
β_3								
τ								
ν x 10^8		0.000016						
		2.55						
δ x 10^5	-0.000023	-0.000036	-0.000022	0.000019	-0.000023	-0.000032	-0.000019	-0.00022
	-1.19	-0.99		1.66	-1.79	-1.95	-1.73	-48.71
log likelihood	4302.6	4128.5	4738.6	4679.3	4354.1	4607.85	4771	4600.6
m_3	0.23	0.237	0.15	0.3	0.31	0.22	0.38	-0.39
m_4	4.03	4.28	4.29	3.83	4.87	4.78	4.9	31.2
Q(20)	32.78	20.86	25.81	24.61	22.69	19.3	25.71	16.43
$Q^2(20)$	13.71	32.45	25.71	14.33	17.99	21.8	18.3	2.1

Table 5 (continued)
GARCH estimates of daily stock returns

	MRSHL	PETKM	THYAO	USAK	VESTL	YKBNK	ISE
$\phi_0 \times 10^3$	0.0023		0.0017	0.0013	0.0037	0.0018	0.002
	2.82		1.71	1.3	5.2	2.08	3.92
ϕ_1				0.044	0.033	0.047	0.12
				2.04	4.68		5.75
ϕ_2		0.04		-0.022			-0.006
		2.12		-1.15			-0.28
ϕ_3	-0.032						0.017
	-1.58						0.87
ϕ_4							0.015
							0.78
ϕ_5							
ϕ_6			-0.028				
			-1.38				
α_0	0.00014	0.00004	0.00038	0.00033	0.0017	0.00031	0.000051
	7.083	5.58	5.088	6.064	12.69	6.92	5.36
α_1	0.2	0.021	0.16	0.122	0.04	0.21	0.18
	7.51	7.95	8.97	8.33	15.96	9.16	10.41
α_2	-0.1	-0.014			0.039		
	-3.63	-5.3			15.96		
β_1	0.85	0.92	0.21	0.77	0.4	0.65	0.82
	51.8	90.4	2.38	31.6	9.66	22.02	9.47
β_2			0.53				-0.5
			6.65				-4.7
β_3							0.45
							8.47
τ							
$\nu \times 10^8$							
$\delta \times 10^5$	-0.000035	0.00001	-0.00011	-0.000049	-0.00067	0.000061	0.0000013
	-2.95	1.43	-2.37	-1.74	-7.64	2.06	0.192
log likelihood	444.975	4296	3957.7	4055.7	4012.57	4398.7	5758.6
m_3	0.27	0.33	0.46	0.25	0.23	0.21	0.008
m_4	4.99	4.08	5.06	4.532	5.33	3.95	4.07
$Q(20)$	13.88	33.59	24.2	19.71	35.4	18.4	28.7
$Q^2(20)$	13.42	16.3	9.95	13.7	806.4	6.76	14.44

Table 6
GARCH estimates of monthly stock returns

	AFYON	DENCM	DEVA	EGGUB	ENKA	EREGL	FENIS	HEKTS
ϕ_0	8.045	7.042	4.52	6.08	9.42	8.22	5.29	7.25
	3.4	2.29	2.62	2.12	2.54	3.046	4.24	1.84
ϕ_1	-0.033	-0.05	0.078	0.26	0.107	-0.1127	0.056	0.017
	-0.31	-0.53		2.33	0.83	-1.06	0.57	
ϕ_2	-0.051				-0.056			
	-0.827				-0.43			
α_0	869.1	2404.93	756.28	709	349.86	725.77	117.49	943.03
	3.7	264000	3.78	10.5	3.053	7.841	4.46	2.87
α_1	0.145	-0.059	3.39	-0.038	-0.105	-0.067	0.36	-0.025
	1.13	-6.26	9.952	-19000	-1.35	-96100	2.32	-32000
β_1	-0.422	-0.739			0.785		-0.24	
	-1.53	-7.73			9.97		-1.33	
δ	-158.24	-916.23	-351.96	-56.21	-135.67	-101.84	399.26	45.64
	-0.71	-4.29	-1.6	-0.5	-38800	-0.682	2.79	0.136
log likelihood	-530.84	-567.07	-611.41	-551.07		-549.07	-505.1	-570.4
m_3	0.417	0.81	2.21	1.46		1.036	0.77	2.54
m_4	3.62	3.45	11.67	7.82		4.63	4.7	15.36
$Q(20)$	21.38	13.15	22.61	18.98		25.52	25.85	15.412
$Q^2(20)$	35.72	17.9	18.23	5.22		19.44	21.58	1.06

Table 6 (continued)
GARCH estimates of monthly stock returns

	INTEM	KLBMO	KONYA	MRDIN	MRSHL	THYAO	YKBNK	ISE
ϕ_0	8.47	4.32	no	10.49	8.08	10.94	9.78	0.058
	2.14	1.77		5.47	2.88	2.81	3.8	3.18
ϕ_1	-0.004	0.232		-0.186	-0.033	0.051	-0.126	0.055
	-0.06	1.91		-1.977	-0.37	0.6	-3.415	0.61
ϕ_2	0.05				0.043			-0.041
	0.53				0.397			-0.37
α_0	822.66	573.29		411.1	518.72	1433.057	924.42	0.033
	1.5	3.29		7.76	4.7	9.725	7.564	4.25
α_1	-0.14	0.2		-0.074	-0.075	-0.067	-0.063	-0.067
	-2.02	1.517		-3.85	-51600	-2.36	-1.063	-55000
β_1	0.39			0.512				
	0.87			3.57				
δ	-207.62	-188.14		-233.7	-17.95	-489.305	-276.73	0.0031
	-0.85	-1.07		-68500	-0.153	-3.029	-1.822	0.36
log likelihood	-562.9	-537		-525.37	-524.2	-575.37	-552.44	42.97
m_3	1.044	0.91		0.72	0.95	1.355	0.78	0.84
m_4	3.804	4.912		4.79	4.87	5.27	4.56	4.96
$Q(20)$	22.1	26.26		26.85	20.3	12.33	17.18	25.8
$Q^2(20)$	12.31	26.02		8.75	8.32	10.29	8.24	31