# The Day-of-the-Week Effect on Return and Volatility in the Turkish Stock Markets 

Macide Çiçek ${ }^{1}$


#### Abstract

This study investigates the presence of the day-of-the-week effect on the return and return volatility of the BIST (Borsa Istanbul) stock indexes, those of the BIST-100, the BIST-Financials, the BIST-Services, the BIST-Industrials, and the BIST-Technology for the period January 7, 2008 to December 28, 2012 in Turkey. Empirical findings obtained from EGARCH $(1,1)$ model show that the returns on Mondays are positive and the highest during the week for all indexes, and only the BIST-Financials index returns do not show the significant Monday effect. There isn't any evidence of the day-of-the-week effect on the BIST-Financials returns. The BIST-100 Industrials returns also show a significant positive Tuesday and Wednesday effects, while the BIST-Technology shows a positive Tuesday effect. On Fridays, all index returns are positive and not significant except the BIST-Services. Return volatility increases the most on Mondays, while decreases the most on Fridays for each index. This is statistically significant for the BIST-100, the BIST-Financials and the BIST-Industrials. On Tuesdays, volatility declines insignificantly in all index returns except the BIST-Industrials. On Wednesdays and Thursdays, there is no significant impact on the volatility. There exists no evidence of the day-of-the-week on the volatility of the BIST-Services and the BIST-Technology returns. This study also finds that the leverage effect exists in all indexes and all of them display strong GARCH effects.


JEL classification numbers: G11, G14, G15
Keywords: The day-of-the-week effect, Return and volatility, Turkish stock markets, BIST, EGARCH $(1,1)$ model

[^0]
## 1 Introduction

The day-of-the-week effect is a phenomenon that the distribution of mean returns varies according to the day of the week in contrast with the Efficient Market Theory in which it is expected that every day of the week should exhibit similar returns and volatility. Put it differently, the day-of-the-week effect builds up a form of anomaly of the Efficient Market Theory. There is a widespread evidence of Monday returns for stock markets are often negative or the lowest (the Monday Effect), ${ }^{2}$ possibly due to the announcement of unfavorable news are released when the markets are closed, causing investors to sell on the coming first trading day. ${ }^{3}$ And, highest volatility occurs on Mondays contrary to common belief of risk-return relationship. ${ }^{4}$ Simultaneously, Friday returns are documented to be positive and the highest of the week (the Friday or Weekend Effect) before the weekend break. ${ }^{5}$ Shortly, stock exchange market starts downwards and ends upwards as informed by [1]. Specifically, the day-of-the-week effect has been seperated into two specific effects, the Monday Effect and a Friday or Weekend Effect, although conceptually the effect is applied to every day of the week. It is clear that stock investors benefit from the existence of significant day-of-the-week effect for profitable trading strategy development in such a manner that buying stocks on the days with low returns and selling stocks on the days with high returns. Accordingly, investors behave differently on different days of the week.
It is noted that the Monday effect was defined at least as at the early 1920s, and [2] and [3] first documented the Monday effect. [1] found that Monday to be the worse day to buy stocks based on three-year statistical study for US market. [3] found statistically significant differences between average Monday returns and Friday returns for US stock market. Yet, attention to this phenomenon arose only after [1] and [4]. Beginning with these studies observed that the average daily return of the market is not the same for all trading days, and that the Monday returns in the US markets are negative, numerous studies have been continued to examine this interesting issue. In empirical finance, testing the day-of-the-week effect as a market anomaly has become an active research topic in both developed and developing markets, while a few studies have considered the Turkish stock markets up to the present. By considering this situation, this study aims to contribute to the empirical literature by analysis on whether there is an evidence of calender effect due to the day of the week on the mean returns and return volatility for the stock market indexes in Turkey on sectoral basis. The sample considered in this study includes the post period of 2007-8 global financial crisis.
This paper organized as follows: Section 2 presents the overview of the literature on the day-of-the-week effect; Section 3 describes the methodology applied and Section 4 outlines the data used. The interpretation of the empirical results are gived in Section 5. This study closes in Section 6 with conclusions.
${ }^{2}$ e.g. [1], [4], [7], [8], [19], [24], [81], [82], [83], [84], [85].
${ }^{3}$ See, for example, [6], [9], [32], [86], [87].
${ }^{4}$ For example, [88] and [1] noticed that Monday's variance was higher than other daily returns.
${ }^{5}$ e.g. [1], [4], [6], [8], [9], [11], [22], [26], [81], [87], [89].

## 2 Literature

In finance literature, the day-of-the-week effect has been researched in stock markets worldwide, although emerging markets have received attention more recently compared to developed markets. The presence of the day-of-the-week regularity previously found in the US stock markets and then on European stock markets. Since the first studies on this effect go back to [2] and [3], numerous papers report on new empirical evidence for and against the day-of-the-week effect. [5] and [1] found different expected S\&P500 returns on Fridays and Mondays. [1] conducted a statistical test and provided evidence that the mean returns of the S\&P500 index on Friday was higher than mean return on Monday for the period 1953 through 1970. [4] examined daily returns for the S\&P500 index over a 25-year period, 1953-1977, and found that the average returns on Monday significantly negative, inconsistent with his calendar time hypothesis which states Monday returns should be higher compared to the other days of the week. He also found that the average returns from Tuesday to Friday were positive and Friday returns were greater than weekly average returns. Similarly, [6], [7] and [8] reported abnormal losses on Mondays relative to other days. [7] went back to the 1920s and studied the S\&P500 returns from 1928-1982. The study of [6] was based on a sample of 30 stocks from the Dow Jones Industrial Index during the period July 2, 1962-December 28, 1978. [8] demonstrated that there are differences in distribution of stock returns across weekdays. [9] studied the period from July 1962 to December 1979 and reported similar results in line with the study of [10], negative returns on Monday and higher returns on Friday. [11] examined the day-of-the-week anomaly for the Dow Jones Industrial Average by conducting a ninety-year study for the period 1897 through 1986. Authors reported negative Monday returns for the entire period and for each of nine subsample period. [12] found significant daily return autocorrelations that vary with the day of the week for the whole period from 1885 to 1989 and each of 10 subperiods for US stock markets. [13] determined that if Monday returns had been equal to the average return for other weekdays over the period 1885 through 1997 period, the Dow Jones Industrial Average almost doubled its level at the end of 1997.
Several studies found weekday effects not only in the US but also in the other developed and emerging markets. For most of the western economies, namely US, the UK, Canada, empirical results have come to the conclusion that statistically significant negative returns occured on Mondays, while statistically significant positive returns on Fridays. However, negative average returns are observed on Tuesdays, such as Japan, Australia, and France. [14] and [15] documented a weekend effect in the Canadian market. [16] observed negative Tuesday returns in the same market. [17] reported evidence of the day-of-the week effect for the UK stock markets. [18] analyzed the British stock market using the FT30 index returns and found that Monday had lower returns compared to other days of the week for the period 1935-1994. [19] found weekday effects similar to those in the US market for the Canadian, British, Japanese and Australian equity markets. Authors reported average returns for Mondays were negative in all cases and lowest returns occurred on Tuesdays in the Japanese and Australian markets. [20] found low Tuesday and high Wednesday returns for the Japanese stock market. The most satisfactory explanation that has been given for significant negative Tuesday effect is that the bad news of the weekend affecting the US's markets influence some markets negatively a day later. Similar results on negative Tuesday effect are found for the Milan Stock Exchange by [21], for the CAC index of Paris Bourse by [22], for the Toronto Stock Exchange by
[16], and for the BIST by [23].
Some studies presented international evidence on the day-of-the-week effect. [24] found significant negative Monday returns in 13 of 23 international markets. [25] studying on stock markets of Australia, Belgium, Brazil, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Luxembourg, Mexico, the Netherlands, New Zealand, Singapore, Sweden, Switzerland, and the UK observed that lower or negative returns on Mondays and Tuesdays, and higher and positive returns from Wednesday to Friday in almost all the countries. [26] provided further evidence of the existence of significant negative Monday returns for the US, the UK, German, Japanese, Australian and Swiss stock markets, among the others, during the period 1969-1992 using standard statistical approaches and moving averages. Authors observed that Wednesdays presented the highest returns while Monday presented the lowest returns for all the above markets except the Japanese and the Australian, and also reported that the effect disappeared in recent periods in US.
[27] studying on 23 European, Asian and North American markets found pervasive weekday effects. On the other hand, [28] and [29] studying on the Spanish stock market found that there is no day-of-the-week effect. Also, [30] reported no weekend effect in the Danish market. The study of [31] for the US markets showed that Monday effect occurs primarily in the fourth and fifth weeks of the month and the mean Monday return of the first three weeks is not significantly different from zero. [32] concluded that speculative short sales contribute to the weekend effect, causing stock prices to rise on Fridays and fall on Mondays.
[33] studying on emerging stock markets in eleven Eastern European countries found that the daily average returns for Mondays for six indexes were negative, and provided an evidence against the Monday effect. [34] analyzing Athens Stock Exchange General Index for the period from October 1986 to April 1997 found the evidence on the day-of-the-week effect for Greece. [35] found negative Monday returns in Czech Republic, France, Italy, Slovakia, Spain, Turkey and the United Kingdom, and negative Wednesday returns in Czech Republic, Germany, Russia, Spain and Sweden for the period of 1997-2004.
For emerging markets in Asia, namely Hong Kong, Singapore, Malaysia, and the Phillippines, [36] found a strong negative Monday effect and a strong negative Tuesday effect. [37] showed significant the day-of-the-week effect in Hong Kong, Thailand, Singapore and Malaysia but not in Taiwan. [38] studied Southeast Asian stock markets, namely the Philippines, South Korea, Malaysia, Singapore, Taiwan and Thailand for the period 1989 to 1996 and found that South Korea and Philippines showed insignificant calendar effects, while Malaysia and Thailand showed significant positive returns on Mondays and significant negative returns on Tuesdays. They also found negative returns on Wednesdays for Taiwan. [39] examining the day-of-the-week effect in Bombay Stock Exchange over the period 1987-1994 found that Friday returns are significantly higher than the other days of the week. However, [40] found no evidence of the existence of the day-of-the-week effect in Indian stock market.
Some studies modelled the day of the week effect using different variations of GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. For instance, [41] investigated the day-of-the-week effect on 7 emerging Asian stock markets, namely India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, and Thailand returns and conditional variance using the GARCH model from January 1990 to June 1995 and found the significant presence of the day-of-the-week effect on both stock returns and volatility. [42] tested daily stock returns for 19 countries using a GJR-GARCH framework and
found significant day-of-the week effect on volatility for 8 countries. [43] modelled the day-of-the-week effect using GARCH models and found that the day-of-the-week effect is present in both volatility and return equations for S\&P500 index during the period of January 1973 to October 1997. Authors observed that the highest returns on Wednesdays and the lowest returns are on Mondays, while the highest volatility on Fridays and the lowest volatility on Wednesdays. [44] investigated the day-of-the-week effect on the volatility of major stock market indexes for the period of 1988 through 2002 using GARCH models and found that the day-of-the-week effect is present in both return and volatility equations. The highest volatility occurs on Mondays for Germany and Japan, on Fridays for Canada and the United States, and on Thursdays for the United Kingdom and the lowest volatility occurs on Mondays for Canada and on Tuesdays for Germany, Japan, the United Kingdom, and the United States. For most of the markets, the authors stated that the days with the highest volatility also accompanied by low trading volume. [45] analyzed the day-of-the-week effect for Germany, Austria, Belgium, Denmark, Spain, France, The Netherlands, Italy, Portugal, the United Kingdom, the Czech Republic, Sweden and Switzerland stock markets over the period July, 21997 through March 22, 2004 by using GARCH and T-ARCH models. Authors concluded that there is no evidence of the day-of-the-week effect in returns, however, there is an evidence in volatility. Also, they stated that Mondays and Thursdays are more uncertain than on Wednesdays, while the Wednesday measure is lower than that of Tuesdays and Fridays in point of seasonality in conditional volatility. [46] found there is day-of-the-week effect on return and volatility equations for Greek stock market by using GARCH ( 1,1 )-M model over the period 1995-2000. Authors observed that Monday returns are smaller than Wednesday returns and the general index has significantly higher volatility on Mondays, among the other indexes. [47] found the day-of-the-week effect for six European countries (Athens, Paris, Helsinki, Dublin, Milan and Zurich), applying a GARCH model to returns and volatility. More recently, [48] found the day-of-the-week effect in volatility in some of the main EU stock markets. Very recently, [49] examined the day-of-the-week effect for six stock markets in Latin America countries, namely in Argentina, Brazil, Chile, Colombia, Mexico, and Peru from 1993 to 2007 applying inclusive of GARCH models and found significant evidence of Monday effect or Friday Effect in many cases.
[50] investigated the day-of-the-week using a GARCH-in-Mean (GARCH-M) model in Africa's largest stock markets and found that there is significant daily seasonality for some of them in both mean returns and volatility and rejected the day-of-the-week effect in Egypt, Kenya, Morocco and Tunisia. [51] analyzing twelve major Arab region asset markets from May, 2002 to December, 2005 by using GARCH-type specifications found that one-third of these markets exhibit significant day-of-the-week effect in returns, two-third of these markets exhibit significant day-of-the-week effect in volatility. [52] investigating the day-of-the-week effect for Sudanese stock market over the period of January 2, 2006 to October 30, 2011 using OLS and GARCH (1,1)-M model found against evidence for the day-of-the-week effect in both returns and conditional variance, in general. The results also indicated that the day-of-the-week effect isn't influenced by the stock market risk.
For the Turkish stock markets, [53] found that the highest returns are obtained on Fridays and the lowest returns on Thursdays between January, 1988 and February, 1992. [54] found significant negative Tuesday returns and positive Friday returns for the period 1990-1992. [55] supported high Friday returns from October, 1990 to December, 1993. [53] and [56] found that there are negative returns on Tuesdays. [23] reported that the
highest returns and the lowest standard deviations on Fridays followed by Wednesdays, and the lowest and negative returns on Tuesdays and the highest standard deviations on Mondays for the period January, 1988 through August, 1994 in Istanbul Securities Exchange Composite index based on a regression model. Author stated that even though the day-of-the-week effect exists, the magnitude and direction of this effect changes over time. [57] found there is a strong Friday effect but insignificant and negative Monday effect. In addition, [58], [59], [60], [61], [62] and [63] all have reported the day-of-the-week effect for the BIST. Among them, [58] studied the BIST-100 and the BIST-30 indexes from 1988 to 1999 using regression model and found that Monday and Tuesday have the lowest returns and Wednesday and Friday have the highest returns significantly in the BIST-100 index. Monday and Tuesday returns are lower again, but highest returns are obtained on Fridays for the BIST-30 Index. [56] confirmed the existence of the day-of-the-week effect for the BIST-100 in the same period using a regression model. [59] investigated the day-of-the-week effect on stock return and volatility for the period of 1986 through 2003 using a GARCH model and documented significant evidence of the day-of-the-week effect both in stock returns and in stock market volatility. According the results of this study, Friday has the highest return with 0,015 while Monday has the lowest return with $-0,003$ compared to return on Wednesday. With respect to volatility, Monday has the highest volatility with 0,933 and Tuesday has the lowest volatility with $-0,716$ compared to volatility on Wednesday. [60] found that Monday has the lowest return and Thursday and Friday have the highest return during the period 1988-2003, supporting the day-of-the-week anomaly. [62] found statistically significant negative returns for Mondays, positive returns for Thursdays and for Fridays from the beginning of 1987 to the end of 2005, employing AR-GARCH-M model. [61] examined the day-of-the-week effect for the BIST-100 index for the period of January 1st, 2002-June 30th, 2005 and for each year, and provided the evidence that the day-of-the-week effect is not present. [63] examined the day-of-the-week effect for the period 2001:07-2007:06 employing GARCH models for the BIST-30, the BIST-100, the BIST-National, the BIST National-Industry, the BIST National-Financial and the BIST National-Services indexes and revealed that the returns on Thursdays and Fridays have been positive and significant in statistical sense. Authors stated that the existence of the day-of-the-week effect can not be explained by variation in the conditional risk. [64] found no evidence of Monday or Tuesday effect in the Turkish stock market for the period 1988-1996 even though the authors noted that Friday returns are statistically different from other days of the week and consistently high. [65] examined 20 emerging stock markets, including Turkey, and found that the lowest returns are on Mondays and the highest returns are on Fridays using EGARCH-M model. Using GARCH $(1,1)$ model, [66] examined the whole period of July 3rd, 1987-July 18th, 2008 and reported that the BIST-100 daily returns on Fridays are higher than the average, while returns on Mondays are lower. [67] studied that short selling activities in relation to the day-of-the-week effect and the weekend effect during the period from 2005 to 2009 in the BIST using OLS. Authors found statistically significant Monday effect and after-holiday effect for short selling, and positive correlation between short selling and returns for all days of the week. [68] examined the day-of-the-week effect for the BIST over the period January 11, 1988 to August 10, 2010 based on stochastic dominance approach. Author concluded that the day-of-the-week effect is limited in the BIST, because none of the days can separately dominate any other even if the results confirm low Monday and Tuesday, high Friday returns.

## 3 Model

To test for reliable evidence of the day-of-the-week effect on both mean returns and return volatility for the Turkish stock markets, the EGARCH (Exponential Generalized Auto-Regressive Conditional Heteroskedasticity) model of Nelson ([69]) is employed in this study. Since the studies of [70] and [71], several variants of GARCH model have been developed to model volatility of financial time series. GARCH-type models are robust to underlying non-normality and encompass an autocorrelation correction. The presence of heteroscedasticity indicates that GARCH modelling is appropriate. The OLS method could be used to detect this effect, but the return distributional characteristics of stock markets don't advocate the use of OLS method, as stated by [72].
The advantages of the EGARCH specification over the basic GARCH spesifications are as follow. Firstly, the non-negativity constraint on the model parameters does not need to be artificially imposed. Secondly, this model captures the negative dynamic asymmetries noticed in many financial time series, i.e., so-called leverage effects. First observed by [73], the leverage effect means that a positive shock has less effect on volatility compared to a negative shock, in other words, volatility tends to rise in response to bad news and fall in response to good news, suggesting that investor's response to shocks is not symmetric. The EGARCH model of [69] accounts for such an asymmetric response to a shock. GARCH specification fails in explaining the leverage effects because assumes the conditional variance responds symmetrically to positive and negative shocks. In order to distinguish several asymmetric effects of a shock to returns successfully, the EGARCH model is preferred in this study. The empirical results also suggest that the EGARCH model fits the data better than the GARCH model in modeling the volatility of the Turkish stock returns. "Figure 1" clearly exhibits volatility clustering and non-normal return distribution, indicating that the asymmetric GARCH models will be more suitable for the return series. Generally, it is expected that the leverage effect to be negative. The other frequently used model of asymmetric behaviour in ARCH-type models is TGARCH model of [74].
When the mean return of a security is dependent on its risk (volatility), the GARCH-M model formulation can be used. In this class of models, the conditional variance (or standart deviation) enters into the volatility equation. In this study, it is wanted to allow the degree of risk aversion (it can be interpreted a risk premium) to change across the days of the week, but then, upon solving the model the risk premium is estimated statistically insignificant, and the EGARCH-M model isn't used.
The GARCH ( $\mathrm{p}, \mathrm{q}$ ) model includes $p$ lags on the conditional variance term and $q$ on the squared error term. However, in practice the model generally used is the GARCH $(1,1)$, that is, $p=q=1$. [75] suggest that the lag order $(1,1)$ is sufficient to capture all volatility clustering that is present in the data. Also, [76] find that the GARCH (1,1) fits well for most financial time series. Thus, the order of $p$ and $q$ considered in this study is 1 . The day-of-the-week effect in both mean and conditional volatility is sensitive to the assumption made about the conditional distribution of the error term because the choice of the error distribution affects the analysis. Normal (Gaussian) distribution, Student's t-distribution, and Nelson's [69] Generalized Error Distribution (GED) are commonly employed when working with ARCH models. Since much financial market data exhibits substantial kurtosis, the variance of stock market returns are better characterized by a conditional Student's t-distribution as a non-normal distribution. Often, the conditionally normality assumption do not captures the thick tails entirely, while conditional Student's
t-distribution and conditional Generalized Error Distribution allow for fatter tails in the conditional distribution. ${ }^{6}$ Therefore, this study assumes that the error distribution follows a conditional Student's t-density function. In estimating the parameters of the EGARCH $(1,1)$ model, the technique of the maximum likelihood estimation was implemented. According to [77], the quasi-maximum likelihood estimator (QMLE) provides asymptotic standard errors that are valid under non-normality.
In order to test the day-of-the-week effect on daily returns and return volatility in Turkish stock indexes, the following EGARCH $(1,1)$ model with dummy variables representing the day-of-the-week effect is estimated:

$$
\begin{align*}
& R_{t}=\varphi_{1} D_{M O N, t}+\varphi_{2} D_{T U E, t}+\varphi_{3} D_{W E D, t}+\varphi_{4} D_{T H U, t}+\varphi_{5} D_{F R I, t}+\eta_{t} \cdot \sum_{i=1}^{n} R_{t-i}+\varepsilon_{t}  \tag{1}\\
& \varepsilon_{t}=\sigma_{t} z_{t}  \tag{2}\\
& z_{t} \mid \Omega_{t-1} \sim \psi(0,1, v)  \tag{3}\\
& \log \sigma_{t}^{2}=\omega+\sum_{j=1}^{p} \beta_{j} \log \sigma_{t-j}^{2}+\sum_{i=1}^{q} \alpha_{i} \mid z_{t-i}-E\left(z_{t-i)} \mid+\sum_{k=1}^{r} \gamma_{k} \log \left(z_{t-k}\right)+\sum_{i=1}^{5} \delta_{i} D_{i, t}\right. \tag{4}
\end{align*}
$$

where $z_{t-i}=\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$.
Equation (1) represents the mean equation, while Equation (4) represents the conditional variance equation. In Equation (1), $R_{t}$ is the daily return for each index, $\varphi_{1}, \varphi_{2}, \varphi_{3}, \varphi_{4}$ and $\varphi_{5}$ are parameters to be estimated, $\varepsilon_{t}$ is a random error term, and $D_{M O N, t}, D_{T U E, t}, \ldots, D_{F R L, t}$ are dummy variables for Monday, Tuesday, ..., Friday. They each take the value of 1 on the respective day of the week and zero otherwise (i.e., $D_{1 t}=1$, if $t$ is Monday, and zero otherwise). In order to avoid the dummy variable trap, the day-of-the-week effect is usually represented by introducing five zero-one dummy variables without the constant term or four zero-one dummy variables plus the constant term. In this study, since all five weekdays are included as dummy variables, the constant term is excluded. $R_{t-i}$ is the lagged values of the return variable, and it is included the equation to eliminate the possibility of having autocorrelated errors and the heteroskedasticity problem. The conditional density function for $z_{t}$ follows Student's t innovation distribution with mean 0 , variance 1 and degrees of freedom $v$. In Equation (4) $\sigma_{t}^{2}$ is known as conditional variance and $z_{t}$ is the standardized shock. $\psi($. marks a conditional density function and $v$ denotes a vector of parameters needed to specify the probability distribution. $\omega, \beta, \alpha, \gamma$ are the parameters to be estimated in Equation (4). The $\alpha$ parameter denotes the magnitude effect or the symmetric effect.

[^1]$\beta$ measures the persistence in conditional volatility. When $\beta$ is relatively large, then volatility takes a long time to die out. The $\gamma$ parameter measures the asymmetry or the leverage effect, and the impact is asymmetric, if $\gamma \neq 0$; and leverage effect is present, if $\gamma<0$. More clearly, when $\gamma<0$, then positive shocks (good news) generate less volatility than negative shocks (bad news). If $\gamma>0$, positive shocks are more destablizing than negative shocks. Also, in order to detect the presence of the day-of-the-week effect in volatility, the conditional volatility equations of equity returns is modelled by including each day trading week dummy variables in the conditional variance equation, followed by [44].

## 4 Data

In this study it is employed daily data obtained from the Borsa Istanbul website for 5 stock market indexes, namely the BIST-100, the BIST-Financials, the BIST-Services, the BIST-Industrials and the BIST-Technology, covering the period January 7, 2008 through December 28, 2012 ( 5 years or 1300 observations on prices). The weeks which have less than five trading days are excluded from the sample in order to isolate any pre-holiday effect. It is known that the stochastic dominance procedure requires each weekly return series has the same number of observations. Thus, it is provided that 1300 observations are equally divided for each day of the week. The sample involves the ongoing 2007-8 global financial crisis period.
The returns of each stock index are computed as the natural logarithmic first difference of each stock index daily closing price, i.e., the daily return, $R_{t}$, is calculated as:

$$
\begin{equation*}
R_{t}=\left(\ln P_{t}-\ln P_{t-1}\right) x 100 \tag{5}
\end{equation*}
$$

where $\ln P_{t}$ and $\ln P_{t-1}$ are the logaritms of each stock index daily price for periods $t$ and $\mathrm{t}-1$, respectively. "Figure 1 " displays the daily returns and the logaritms of index values for each index.




Figure 1: Index returns and logaritms of index values
In order to check the stationarity as a fundamental characteristic in the time series, the Augmented Dickey-Fuller (ADF) ([78]) and the Phillips-Perron (PP) ([79]) tests are applied using a maximum lag of 28 days stationarity. "Table 1 " reports the results of the ADF and PP unit root tests for 5 stock indexes for levels (log of price series) and the first differences of the natural log values (return series). Since the ADF and PP statistics are greater than -3.4351 of the $1 \%$ critical value, the null hypothesis of non-stationary is not rejected in the price series. The null hypothesis of non-stationarity is rejected for all return series, since the t -statistics are highly negative and lower than the $1 \%$ critical value. These findings confirm that all the stock indexes are non-stationary in their levels and become stationary when they are first differenced. In short, return series are stationary.

Table 1: ADF and PP test results for unit roots

|  | ADF Test Statistics |  | PP Test Statistics |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Levels | First Differences | Levels | First Differences |
| BIST-100 | -0.192 | $-34.681^{* * *}$ | -0.242 | $-34.670^{* * *}$ |
| BIST-Financials | -0.521 | $-35.064^{* * *}$ | -0.556 | $-35.059^{* * *}$ |
| BIST-Services | -0.216 | $-35.630^{* * *}$ | -0.152 | $-35.643^{* * *}$ |
| BIST-Industrials | -0.030 | $-31.916^{* * *}$ | 0.014 | $-31.919^{* * *}$ |
| BIST-Technology | -0.029 | $-34.181^{* * *}$ | -0.073 | $-34.151^{* * *}$ |

Notes: The $1 \%$ critical value of the ADF and PP statistics for all indexes is -3.4351 both in levels and in first differences. ${ }^{* * *}$ implies significance at the $1 \%$ level.

These results indicates that the stock indexes under consideration in Turkey behave as random walks, supporting the weak-form of the Efficient Market Hypothesis which says financial time series exhibit a behaviour as random walks. In other saying, past stock index values cannot be used to predict future stock index values. For this reason, stock market participants cannot devise any statistical technique to earn from their tradings continually.
Descriptive statistics for each index returns are presented in "Table 2". The mean returns of each index are positive for the period considered, and the BIST-Technology index has the highest returns among the mean returns. The BIST-Financials index has the maximum return of $14.1 \%$ and the minimum return of $-10.8 \%$. The BIST-Industrials index has the lowest returns among the maximum returns, and the BIST-Services index provides minimum loss. The BIST-Financials index has the highest standart deviation of 2.15 compared to the other indexes, while the BIST-Services index has the lowest.

Table 2: Descriptive statistics on return series

|  | BIST-100 | BIST-Fin. | BIST-Serv. | BIST-Ind. | BIST-Tech. |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Mean | 0.03 | 0.02 | 0.03 | 0.03 | 0.07 |
| Med. | 0.03 | 0.00 | 0.00 | 0.09 | 0.07 |
| Max. | 12.12 | 14.12 | 9.99 | 8.38 | 10.75 |
| Min. | -9.01 | -10.87 | -6.80 | -9.62 | -10.11 |
| S. Dev. | 1.80 | 2.15 | 1.47 | 1.49 | 1.89 |
| Skew. | -0.12 | -0.06 | 0.06 | -0.72 | -0.30 |
| Kurt. | 7.11 | 6.86 | 7.09 | 8.40 | 6.26 |
| JB | $917.9^{\mathrm{a}}(0.00)$ | $808.2^{\mathrm{a}}$ | $(0.00)$ | $908.3^{\mathrm{a}}$ | $1691.6^{\mathrm{a}}$ |

Notes: ${ }^{\text {a }}$ implies significance at the $1 \%$ level. Figures in parentheses are the p-values for Jarque-Bera (JB) normality test.
"Table 2 " also reports skewness and excess kurtosis for the return series of each market. A skewness value more or less than zero refers to asymmetry of the distribution, and negative skewness values suggest that there is a significant asymmetric response to negative shocks while positive values suggest that there is significant asymmetric
response to positive shocks. Skewness for the BIST-100, the BIST-Financials, the BIST-Industrials and the BIST-Technology returns show a negative value, indicating that these indexes show asymmetric response to negative shocks. The BIST-Services index returns are positively skewed, indicating that the distribution of the series has a long right tail. All the index returns exhibit high level of kurtosis, indicating that these distributions are flatter than the normal distribution. The normal distribution value is 3 and the returns that are close to normal distribution is the BIST-Technology returns. So, the distributions are leptokurtic. These findings are further strengthened by Jarque-Bera (JB) normality test. All the Jarque-Bera test results are significant at the $1 \%$ level, so the return series is non-normally distributed.
Before modeling the returns by a GARCH model, detecting the presence of GARCH process is neccessary. So then, some qualitative and quantitative checks can be performed on the data. For qualitative checks, plots of the sample autocorrelation function (ACF) and the partial-autocorrelation function (PACF) on the returns are obtained, and the Ljung-Box Q-test ([80]) and the Engle's ARCH test ([70]) are employed for quantitative checks.
In order to check for autocorrelation (ACF) in the residuals and the squared residuals of return series, the correlogram of the residuals and the correlogram of squared residuals for each stock index are displayed in "Figure 2" and "Figure 3", respectively. The lag is shown along the horizontal axis and the autocorrelation is on the vertical axis. The number of autocorrelation lags equals 28.
Since visual inspection shows that the plotted residuals that are greater than 2 standard errors away from the zero correlation at most of the lags, more of the autocorrelations are significantly non-zero, indicating that statistically significant autocorrelation in "Figure 2". However, for example, there appears to be no significant autocorrelation in the residuals of the BIST-100 index returns at lag 1, 2, 3, 5, 9, 14, 15, 16, 20, 22, 23, 24, 25, 26, and 27.

Looking at the "Figure 3", it can be seen that there are significant deviations from zero mean at almost all lags, and therefore the null hypothesis of "No Autocorrelation" is rejected in the squared residuals for all indexes.
These results reveal that the presence of a non-stationary variance process in the return series, suggesting that a GARCH model may be appropriate. The partial-autocorrelation (PACF) functions also present quite similar results, hence they haven't been shown as a graph here.





Figure 2: Correlogram of residuals



Figure 3: Correlogram of squared residuals
Although still the autocorrelation has been detected visually via the graphs, it is needed to quantify the autocorrelation. For that purpose, the Ljung-Box Q-test and the Engle's ARCH test are performed. The Ljung-Box (LB) Q-test results applied on the residuals of the returns and the squared residuals of the returns are summarized in "Table 3 " and "Table 4", respectively.

Table 3: Ljung-Box Q-Test on return series

| Lags | BIST-100 | BIST-Fin. | BIST-Serv. | BIST-Ind. | BIST-Tech. |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | $0.000(0.98)$ | $8 . \mathrm{E}-05(0.99)$ | $0.000(0.98)$ | $0.002(0.96)$ | 0.000 <br> $(0.98)$ |
| 5 | $1.323(0.93)$ | $2.573(0.76)$ | $3.088(0.68)$ | $2.888(0.71)$ | 9.171 <br> $(0.10)$ |
| 10 | $12.09(0.27)$ | $14.49(0.15)$ | $7.032(0.72)$ | $16.02^{*}(0.09)$ | $22.17^{* *}(0.01)$ |
| 15 | $24.15^{*}(0.06)$ | $30.00^{* *}(0.01)$ | $15.86(0.39)$ | $23.47^{*}(0.07)$ | $26.39^{* *}(0.03)$ |
| 20 | $33.95^{* *}$ <br> $(0.02)$ | $42.91^{* * *}$ <br> $(0.00)$ | $19.65(0.48)$ | $33.10^{* *}$ <br> $(0.03)$ | $32.07^{* *}(0.04)$ |
| 25 | $35.74^{*}(0.07)$ | $45.47^{* * *}$ <br> $(0.00)$ | $25.67(0.42)$ | $34.69^{*}(0.09)$ | $36.09^{*}(0.07)$ |

Notes: Figures in parentheses are the p-values. ${ }^{* * *}$, ** and ${ }^{*}$ imply significance at the $1 \%, 5 \%$ and $10 \%$ level, respectively.

Table 4: Ljung-Box Q-Test on squared return series

| Lags | BIST-100 | BIST-Fin. | BIST-Serv. | BIST-Ind. | BIST-Tech. |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | $17.4^{* * *}$ | $12.5^{* * *}$ | $34.9^{* * *}$ | $48.90^{* * *}$ | $31.7^{* * * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |
| 5 | $182.2^{* * * *}$ | $183.7^{* * * *}$ | $116.3^{* * *}$ | $205.7^{* * *}$ | $137.7^{* * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |
| 10 | $264.6^{* * * *}$ | $284.0^{* * * *}$ | $161.3^{* * *}$ | $252.4^{* * *}$ | $143.5^{* * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |
| 15 | $391.3^{* * * *}$ | $437.3^{* * *}$ | $248.5^{* * *}$ | $332.4^{* * *}$ | $185.9^{* * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |
| 20 | $479.4^{* * * *}$ | $545.3^{* * *}$ | $297.0^{* * *}$ | $389.6^{* * *}$ | $194.7^{* * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |
| 25 | $525.9^{* * * *}$ | $594.9^{* * * *}$ | $360.1^{* * *}$ | $403.9^{* * *}$ | $196.5^{* * *}$ |
|  | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ | $(0.00)$ |

Notes: Figures in parentheses are the p-values. ${ }^{* * *}$ implies significance at the $1 \%$ level.

According to the results given in "Table 3", the null hypothesis of "No Autocorrelation" is rejected in case of the standardized residuals for four indexes except for the BIST-Services. According to "Table 4", the null hypothesis is strongly rejected in case of the square of the residuals for $1,5,10,15,20$, and 25 lags of the ACF at the level of $1 \%$ significance for all indexes. These results indicate that serial correlation is present in the squared returns for each index, suggesting that a significant evidence in support of the ARCH effect. Therefore, a GARCH model is applicable and captures such dependence in the return series.
The Engle's ARCH test also known as Lagrange Multiplier (LM) test results are summarized in "Table 5". This test is one popular method of testing for ARCH or GARCH effect in the return series. The results show that the null hypothesis of "No ARCH effect" against the alternative hypothesis of existence of heteroskedasticity is strongly rejected for all the return series at the $1 \%$ significance level. There is a highly significant evidence supporting the presence of ARCH effect tested for up to order 1,5 , 10 , and 20 lags and the time series has no random sequence of Gaussian (Normal) disturbance, indicating that time varying conditional heteroskedasticity in the return series. "Figure 4 " plots the return volatility series for all indexes.

Table 5: Engle's ARCH Test

| Lags | BIST-100 | BIST-Fin. | BIST-Serv. | BIST-Ind. | BIST-Tech. |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | $17.6^{* * *}$ <br> $(0.00)$ | $12.6^{* * *}$ <br> $(0.00)$ | $35.7^{* * *}$ <br> $(0.00)$ | $50.6^{* * *}$ <br> $(0.00)$ | $32.4^{* * *}$ <br> $(0.00)$ |
|  | $26.5^{* * *}$ <br> $(0.00)$ | $28.9^{* * *}$ <br> $(0.00)$ | $16.1^{* * *}$ <br> $(0.00)$ | $26.1^{* * *}$ <br> $(0.00)$ | $19.4^{* * *}$ <br> $(0.00)$ |
| 10 | $16.0^{* * *}$ <br> $(0.00)$ | $17.4^{* * *}$ <br> $(0.00)$ | $9.8^{* * *}(0.00)$ | $15.0^{* * *}$ <br> $(0.00)$ | $10.5^{* * *}$ <br> $(0.00)$ |
|  | $10.8^{* * *}$ <br> $(0.00)$ | $12.6^{* * *}$ <br> $(0.00)$ | $7.0^{* * *}(0.00)$ | $8.7^{* * *}$ <br> $(0.00)$ | $6.4^{* * *}(0.00)$ |

Notes: Figures in parentheses are the p-values. *** implies significance at the $1 \%$ level.


Figure 4: Volatility of return series

## 5 Empirical Results

"Table 6" presents the estimated EGARCH $(1,1)$ model results assuming the Student's t-distribution for the BIST-100, the BIST-Financials, the BIST-Services, the BIST-Industrials and the BIST-Technology index returns and return volatility. The existence of the day-of-the-week effect is investigated not only in the mean but also in variance. Panel A of "Table 6" shows the estimates for mean equation, while Panel B displays the conditional variance equation estimates.

Table 6: EGARCH $(1,1)$ model results

| Panel A: Mean equations |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | BIST-100 | BIST-Fin. | BIST-Serv. | BIST-Ind. | BIST-Tech. |
| $\varphi_{1}$, Mon | 0.17* | 0.15 | 0.15** | 0.21*** | 0.30*** |
|  | (0.06) | (0.15) | (0.03) | (0.00) | (0.00) |
|  | [0.09] | [0.11] | [0.07] | [0.07] | [0.10] |
| $\varphi_{2}$, Tue | 0.11 | 0.09 | 0.04 | 0.20*** | 0.17** |
|  | (0.17) | (0.35) | (0.48) | (0.00) | (0.04) |
|  | [0.08] | [0.10] | [0.07] | [0.06] | [0.08] |
| $\varphi_{3}$, Wed | 0.07 | 0.08 | -0.02 | 0.11* | 0.04 |
|  | (0.42) | (0.42) | (0.66) | (0.08) | (0.57) |
|  | [0.79] | [0.11] | [0.06] | [0.06] | [0.08] |
| $\varphi_{4}$, Thu | 0.09 | 0.08 | 0.09 | 0.10 | 0.08 |
|  | (0.31) | (0.44) | (0.17) | (0.10) | (0.33) |
|  | [0.08] | [0.10] | [0.07] | [0.06] | [0.08] |
| $\varphi_{5}, \quad$ Fri | 0.05 | 0.00 | 0.14** | 0.08 | 0.03 |
|  | (0.51) | (0.99) | (0.03) | (0.14) | (0.68) |
|  | [0.07] | [0.09] | [0.06] | [0.05] | [0.08] |
| $\eta$ | 0.03 | 0.02 | 0.01 | 0.06** | 0.05* |
|  | (0.23) | (0.38) | (0.61) | (0.02) | (0.07) |
|  | [0.02] | [0.02] | [0.02] | [0.02] | [0.02] |
| Panel B: Variance equations |  |  |  |  |  |
| $\omega$ | $-0.07 * *$ | -0.07*** | -0.04 | -0.07* | -0.12** |
|  | (0.01) | (0.00) | (0.15) | (0.05) | (0.03) |
|  | [0.02] | [0.02] | [0.03] | [0.03] | [0.05] |
| $\beta$ | 0.97*** | 0.98*** | 0.97*** | 0.96*** | 0.90*** |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
|  | [0.00] | [0.00] | [0.00] | [0.00] | [0.02] |
| $\alpha$ | 0.16*** | 0.15*** | 0.13*** | 0.22*** | 0.37*** |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
|  | [0.02] | [0.02] | [0.02] | [0.03] | [0.05] |
| $\gamma$ | -0.07*** | -0.06*** | -0.07*** | -0.09*** | -0.07** |
|  | (0.00) | (0.00) | (0.00) | (0.00) | (0.02) |
|  | [0.01] | [0.01] | [0.01] | [0.02] | [0.03] |
| $\delta_{1}$, Mon | 0.21* | 0.22* | 0.14 | 0.33** | 0.18 |
|  | (0.08) | (0.06) | (0.29) | (0.01) | (0.21) |
|  | [0.12] | [0.12] | [0.13] | [0.14] | [0.14] |
| $\delta_{2}$, Tue | -0.14 | -0.15 | -0.10 | -0.29* | -0.18 |
|  | (0.33) | (0.28) | (0.50) | (0.05) | (0.25) |
|  | [0.14] | [0.14] | [0.15] | [0.15] | [0.16] |
| $\delta_{3}$, Wed | 0.02 | 0.09 | -0.21 | 0.02 | -0.10 |
|  | (0.88) | (0.56) | (0.18) | (0.89) | (0.51) |
|  | [0.15] | [0.15] | [0.16] | [0.16] | [0.16] |
| $\delta_{4}$, Thu | -0.01 | 0.02 | 0.13 | -0.11 | 0.02 |
|  | (0.96) | (0.88) | (0.37) | (0.44) | (0.85) |
|  | [0.14] | [0.14] | [0.15] | [0.15] | [0.15] |
| $\delta_{5}, \quad$ Fri | -0.27** | -0.29** | -0.19 | -0.33** | -0.10 |
|  | (0.04) | (0.02) | (0.14) | (0.02) | (0.46) |
|  | [0.13] | [0.13] | [0.13] | [0.14] | [0.14] |

$\qquad$

| Panel C: Diagnostic checking |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| ARCH-LM statistics |  |  |  |  |  |
| 1 Lag | 0.60 | 0.20 | 7.72*** | 2.25 | 0.76 |
|  | (0.43) | (0.65) | (0.00) | (0.13) | (0.38) |
| 5 Lags | 2.11* | 2.25** | 1.64 | 1.50 | 0.58 |
|  | (0.06) | (0.04) | (0.14) | (0.18) | (0.71) |
| 10 Lags | 1.64* | 1.37 | 1.20 | 1.61* | 0.86 |
|  | (0.08) | (0.18) | (0.27) | (0.09) | (0.56) |
| 20 Lags | 1.08 | 1.19 | 0.83 | 1.12 | 0.97 |
|  | (0.36) | (0.24) | (0.67) | (0.31) | (0.48) |
| Ljung-Box $Q^{2}$-statistics |  |  |  |  |  |
| 1 Lag | 0.60 | 0.19 | 7.69*** | 2.24 | 0.76 |
|  | (0.43) | (0.658) | (0.00) | (0.13) | (0.38) |
| 5 Lags | 10.93* | 11.74** | 8.14 | 7.69 | 2.81 |
|  | (0.05) | (0.03) | (0.14) | (0.17) | (0.72) |
| 10 Lags | 16.29* | 14.51 | 11.54 | 16.43* | 8.13 |
|  | (0.09) | (0.15) | (0.31) | (0.08) | (0.61) |
| 20 Lags | 21.95 | 24.01 | 16.38 | 22.43 | 19.16 |
|  | (0.34) | (0.24) | (0.69) | (0.31) | (0.51) |

Notes: ${ }^{* * *}$, ** and $*$ denote significance at 1,5 and $10 \%$ levels, respectively. Numbers in normal brackets are the p -values and numbers in square brackets are the standart errors.

As is seen from the Panel A of "Table 6", the estimated coefficients of the Monday's dummy variables for all indexes are positive and statistically significant at the $1 \%$ level for the BIST-Industrials and the BIST-Technology, at the $5 \%$ level for the BIST-Services, and at the $10 \%$ level for the BIST-100, suggesting that the mean returns on Monday are higher than those observed on the other days. This evidence is not in favor of the Monday effect which states Monday has the lowest or negative mean returns. The evidence of the day-of-the-week effect isn't found in the mean equation for the BIST-Financials, given that the coefficients of all the dummy variables for this index is not statistically significant. From this point of view, it can be said that the Efficient Market Hypothesis is not rejected for the BIST-Financials index returns, or in other words, the BIST-Financials index is efficient regarding the returns. Since the significant predictability of returns is found somehow for the other four indexes, the Efficient Market Hypothesis may be rejected for them. There is also a significant Tuesday effect in the BIST-Industrials and in the BIST-Technology returns at the $1 \%$ and $5 \%$ level, respectively. These index returns are positive on Tuesdays like Mondays. The one-lagged values of return variable is found significant only in these two indexes. The BIST-Industrials returns are also positive on Wednesdays at the $10 \%$ significance level. However, there is no trustworthy evidence to refer that the mean return for Wednesdays (except the BIST-Industrials) and for Thursdays differs from the other weekdays, because the individual dummy variables are not statistically significant. On Fridays, all index returns are positive, but only the BIST-Services index returns are statistically significant (at the $5 \%$ level). When compared to Fridays, the average returns on Mondays are higher than on Fridays and also on Tuesdays during the study period.
Contrary to the most of the day-of-the-week literature, significant positive parameter estimates for Mondays are observed in the Turkish stock markets. On the other hand, statistically significant positive returns on Fridays which only achieved from the BIST-Services index are in accordance with the literature. The Turkish stock indexes
follow the general pattern of the highest positive returns in the beginning of the week, the lowest positive returns at the end of the week. The empirical results of this study don't coincide with previous research that has been performed on the Turkish stock markets. This is possibly related to the different study period.
From the Panel B of "Table 6", it can be seen that the estimated coefficients of the Monday's variance dummy variable for all indexes are positive and the highest volatility occurs on Mondays for the BIST-Industrials returns at the $5 \%$ significance level. The Monday's variance dummies of the BIST-Financials and the BIST-100 index are also statistically significant at the $10 \%$ level. On Fridays, all dummy variable coefficients are negative but significant only for the BIST-100, the BIST-Financials and the BIST-Industrials index returns, suggesting that return volatility is lower on Fridays than the other weekdays. The largest decrease in volatility is observed in the BIST-Industrials. For Wednesdays and Thursdays, the evidence of the day-of-the-week effect cannot be found for any index in the conditional variance equation. On Tuesdays, all dummy variable coefficients are negative, suggesting that the volatility of the index returns are lower on this day, but this is statistically significant only for the BIST-Industrials at the $10 \%$ level.
To summarize, the day of the day of the week effect is present both in the mean equations (with the exception of the mean equation of BIST-Financials index) and the variance equations (with the exception of the variance equation of the BIST-Services returns and the variance equation of the BIST-Technology returns). It must be stated that when the EGARCH $(1,1)$ model with a GED distribution is estimated, the results are similar to those obtained from Student's t-distribution.
Regarding the relationship between stock market returns and volatility, it can be seen from Panel A and B of "Table 6" that this relationship is positive on Mondays, while negative on Fridays for Turkish stock markets. The relationship between return and volatility in Turkish stock markets is mixed as documented in the literature.
The estimated coefficient of the constant term for the conditional variance equation, $\omega$, is significant for all indexes except for the BIST-Services. $\beta$ and $\alpha$ are the estimated coefficient of the lagged value of the conditional variance and the lagged value of the squared residual term, respectively. Each of these coefficients is positive and significant at the $1 \%$ level. This evidence satisfies the nonnegativity of the conditional variances. Since the $\beta$ coefficients are quite high, the response functions to shocks are likely to die slowly. The coefficient of asymmetry or leverage effect, $\gamma$, is negative as expected and highly significant for all indexes, indicating the existence of the leverage effect in returns during the period. It means that negative shocks increase volatility more than positive shocks of same magnitude in Turkish stock markets.
Panel C of "Table 6" reports the Engle's ARCH-LM tests on the standardized residuals and the Ljung-Box $\mathrm{Q}^{2}$-statistics for the standardized squared residuals of five EGARCH $(1,1)$ models at $1,5,10$, and 20-day lags. The results of these diagnostic tests show that the EGARCH $(1,1)$ models are correctly specified, providing that strong support for the absence of autocorrelation and the EGARCH $(1,1)$ model with Student's t-innovations is enough to remove the dependence in the return series. The results of ARCH-LM tests show no evidence of the remaining ARCH effects (or the presence of heteroskedasticity) for most of the lags, suggesting that the EGARCH $(1,1)$ process is successful at modeling the conditional variance of each index returns. However, for the BIST-Services index the ARCH-LM test indicates that the standardized residuals exhibit ARCH effects up to 1 lag and the residuals display significant autocorrelation up to the 1 st order at the $1 \%$
significance level. According to the most of the Ljung-Box $\mathrm{Q}^{2}$-statistics, the null hypothesis of no autocorrelation is rejected for all indexes.

## 6 Conclusion

This study examines the day-of-the-week effect anomaly in Turkish stock markets on sectoral basis for the period January 7, 2008 through December 28, 2012 using EGARCH $(1,1)$ model. It is generally observed that there is decreasing returns day by day from Mondays to Wednesdays, increasing returns on Thursdays, and again decreasing returns on Fridays. The results reveal that the day-of-the-week effect is present both in return equations (except the BIST-Financials) and in volatility equations (except the BIST-Services and the BIST-Technology).
There exists an evidence of the inverted Monday effect in the BIST-100, the BIST-Services, the BIST-Industrials, and the BIST-Technology index returns. There is no evidence of the day-of-the-week effect for the BIST-Financial index returns, having the meaning for this market is efficient. Monday returns are the highest compared to the other weekdays for all indexes. A positive Tuesday effect is also evident for the BIST-Industrials and the BIST-Technology index returns. Regarding manifacturing, this study also finds abnormal positive returns on Wednesday for the BIST-Industrials. In respect to the mean equations, the presence of the day-of-the-week effect in most of the week for the BIST-Industrials leads to conclusion that the BIST-Industrials is the most inefficient market among the all. Also, it would seem that the second one is the BIST-Technology and the third one is the BIST-Services. The returns on Thursdays are positive but insignificant for all indexes, indicating that there exists no evidence of the Thursday effect. This may implies that each market is working effectively on Thursdays. Only the BIST-Services index returns are significant on Fridays, although still all index returns are positive on this day. The lowest returns are on Fridays except the BIST-Services. The positive returns on Fridays are quite lesser than on Mondays.
As a whole, the volatility in returns increases the most on Mondays while decreases the most on Fridays. The highest volatility in returns on Mondays occurs in the BIST-Industrials and this index is the one that the return volatility decreases the most on Fridays. The BIST-Financials and the BIST-100 follow the BIST-Industrials both in increases and decreases. So, the BIST-Financials is inefficient in respect to volatility, though it is efficient in respect to returns. Volatility declines for each index on Tuesdays, but only the BIST-Industrials has the significant volatility declines. On Wednesdays and Thursdays, there isn't any significant the day-of-the-week effect on the return volatility of any index. Also, there isn't any evidence of the day of the week on the volatility of the BIST-Services and the BIST-Technology returns on no day, bringing to mind these markets are efficient regarding volatility. The results also indicate that bad news have greater effect on return volatility than good news, and volatility shocks are quite persistent.
In comparison with the previous research on the Turkish stock markets and most of the literature, this study shows that the day-of-the-week effect on the return and volatility has changed a lot in Turkey during the ongoing global financial crisis of 2007-8, especially through the finding of the Monday has the highest positive returns.

## References

[1] F. Cross, The behaviour of stock prices on Mondays and Fridays, Financial Analysts Journal, November-December, (1973), 67-69.
[2] F. Kelly, Why you win or lose: The psychology of speculation, Houghton Mifflin, Boston, 1930.
[3] M. J. Fields, Stock prices: A problem in verification, Journal of Business, 7, (1931), 415-418.
[4] K. R. French, Stock returns and the weekend effect, Journal of Financial Economics, 8, (1980), 55-69.
[5] M. Osborne, Periodic structure in the Brownian motion of stock prices, Operations Research, 10, (1962), 267-290.
[6] M. R. Gibbons and P. Hess, Day of the week effects, Journal of Business, 54, (1981), 579-596.
[7] D. B. Keim and F. Stambaugh, A further investigation of weekend effects in stock returns, Journal of Finance, 39, (1984), 819-840.
[8] R. J. Rogalski, New findings regarding day-of-the-week returns over trading and non-trading periods: A note, Journal of Finance, 39, (1984), 1603-1614.
[9] J. Lakonishok and M. Levi, Weekend effects on stock returns: A note, Journal of Finance, 37, (1982), 883-889.
[10] M. Smirlock and L. Starks, Day of the week and intraday effects in stock returns, Journal of Financial Economics, 17, (1986), 197-210.
[11] J. Lakonishok and S. Smidt, Are seasonal anomalies real? A ninety-year perspective, Review of Financial Studies, 1, (1988), 403-425.
[12] H. Bessembinder and M. G. Hertzel, Return autocorrelations around nontrading days, Review of Financial Studies, 6, (1993), 155-189.
[13] J. Siegel, Stocks for the Long Run, McGraw Hill, New York, 1998.
[14] S. Hindmarch, D. Jentsch and D. Drew, A note on Canadian stock returns and the weekend effect, Journal of Business Administration, Vancouver, 14(2), (1984), 163-172.
[15] C. B. Cadsby, Canadian calendar anomalies and the asset pricing model, in A Reappraisal of the Efficiency of Financial Markets. R. M. C. Guimaraes, B. G. Kingsman and S. J. Taylor (eds.), Springer-Verlag, Berlin, (1989), 199-266.
[16] G. Athanassakos and M. J. Robinson, The day of the week anomaly: The Toronto Stock Exchange experience, Journal of Business Finance and Accounting, 21, (1994), 833-856.
[17] P. F. Pope and P. K. Yadav, The impact of option expiration on underlying stocks: The UK evidence, Journal of Business Finance and Accounting, 19, (1992), 329-344.
[18] Z. Arsad and J. A. Coutts, Security price anomalies in the London International Stock Exchange: A 60 year perspective, Applied Financial Economics, 7, (1997), 455-464.
[19] J. Jaffe and R. Westerfield, The week-end effect in common stock returns: The international evidence, Journal of Finance, 40, (1985), 433-454.
[20] K. Kato, Behaviour of Japanese stock price and anomalies, Japanese Economic Journal, 36, (1990), 1031-1044.
[21] E. Barone, The Italian stock market, Journal of Banking and Finance, 14(3), (1990), 431-439.
[22] B. Solnik and L. Bousquet, Day of the week effect on the Paris Bourse, Journal of Banking and Finance, 14, (1990), 461-468.
[23] E. Balaban, Day of the week effects: New evidence from an emerging market, Applied Economics Letters, 2(5), (1995), 139-143.
[24] Eric C. Chang, J. Michael Pinegar and R. Ravichandran, International evidence on the robustness of the day-of-the-week effect, The Journal of Financial and Quantitative Analysis, 28(4), (1993), 497-513.
[25] Agrawal and K. Tandon, Anomalies or illusions? Evidence from stock markets in eighteen countries, Journal of International Money and Finance, 13, (1994), 83-106.
[26] M. Dubois and P. Louvet, The day of the week effect: The international evidence, Journal of Banking and Finance, 20, (1996), 1463-1484.
[27] W. Tong, International evidence on weekend anomalies, The Journal of Financial Research, 23(4), (2000), 495-522.
[28] M. Santemases, An investigation of the Spanish stock market seasonalities, Journal of Business, Finance and Accounting, 13(2), (1986), 267-276.
[29] J. I. Pena, Daily seasonalities and stock market reforms in Spain, Journal of Financial Economics, 5, (1995), 419-423.
[30] P. Jennergren and B. Sorensen, Random walks and anomalies on the Copenhagen Stock Exchange in the 1890s, in A Reappraisal of the Efficiency of Financial Markets. R. M. C. Guimaraes, B. G. Kingsman and S. J. Taylor (eds.), Springer-Verlag, Berlin, (1989), 261-284.
[31] K. Wang, Y. Li and J. Erickson, A new look at the Monday Effect, The Journal of Finance, 52(5), (1997), 2171-2186.
[32] H. Chen and V. Singal, Role of speculative short sales in price formation: The case of the weekend effect, The Journal of Finance, 58(2), (2003), 685-706.
[33] R. A. Ajayi, S. Mehdian and M. J. Perry, The day-of-the week effect in stock returns: Further evidence from Eastern European emerging markets, Emerging Markets Finance and Trade, 40(4), (2004), 53-62.
[34] T. C. Mills, C. Siriopoulos, R. N. Markellos and D. Harizanis, Seasonality in the Athens Stock Exchange, Applied Financial Economics, 10(2), (2000), 137-142.
[35] C. C. Ndu, Stock market returns analysis, day-of-the-week effect, volatility of returns: Evidence from European financial markets 1997-2004, International Research Journal of Finance and Economics, 1, (2006), 112-124.
[36] R. Aggarwal and P. Rivoli, Seasonal and day of the week effects in four emerging stock markets, Financial Review, 24, (1989), 541-550.
[37] [37] K. A. Wong, T. K. Hui and C. Y. Chan, Day-of-the-week effect: Evidence from the developing stock markets, Applied Financial Economics, 2, (1992), 49-56.
[38] C. Brooks and G. Persand, Seasonality in Southeast Asian stock markets: Some new evidence on day-of-the-week effects, Applied Economics Letters, 8, (2001), 155-158.
[39] S. Poshakwale, Evidence on weak form efficiency and day of the week effect in the Indian stock market, Finance India, 10, (1996), 605-616.
[40] B. Bodla and J. Kiran, Seasonal anomalies in stock returns: Evidence from India and the US, Decision, 33(1), (2006), 163-178.
[41] T. Choudhry, Day of the week effect in emerging Asian stock markets: Evidence from the GARCH model, Applied Financial Economics, 10(3), (2000), 235-242.
[42] E. Balaban, A. Bayar and O. B. Kan, Stock returns, seasonality and asymmetric conditional volatility in world equity markets, Applied Economics Letters, 8(4), (2001), 263-268.
[43] H. Berument and H. Kiymaz, The day of the week effect on stock market volatility, International of Economics and Finance, 25(2), (2001), 181-193.
[44] H. Kiymaz and H. Berument, The day of the week effect on stock market volatility and volume: International evidence, Review of Financial Economics, 12, (2003), 363-380.
[45] Rosa María Cáceres Apolinario, Octavio Maroto Santana, Lourdes Jordán Sales and Alejandro Rodríguez Caro, Day of the week effect on European stock markets, International Research Journal of Finance and Economics, 2, (2006), 53-70.
[46] D. Kenourgios and A. Samitas, The day of the week effect patterns on stock market return and volatility: Evidence for the Athens Stock Exchange, International Research Journal of Finance and Economics, 15, (2008), 78-89.
[47] Charles, Does the day-of-the-week effect on volatility improve the volatility forecasts?, Applied Economics Letters, 17(3), (2010), 257-262.
[48] K. Hogholm, J. Knif and S. Pynnoonen, Common and local asymmetry and day-of-the-week effects among EU equity markets, Quantitative Finance, 11(2), (2011), 219-227.
[49] W. K. Rodriguez, Day of the week effect in Latin American stock markets, Revista de Analisis Economico, 27(1), (2012), 71-89.
[50] P. Alagidede, Day of the week seasonality in African stock markets, Applied Financial Economics Letters, 4, (2008), 115-120.
[51] Kamaly and E. A. Tooma, Calendar anomalies and stock market volatility in selected Arab stock exchanges, Applied Financial Economics, 19, (2009), 881-892.
[52] S. Z. S. Abdalla, Day-of-the-week effect on returns and conditional volatility: Empirical evidence from Sudanese stock market, Middle Eastern Finance and Economics, 16, (2012), 167-180.
[53] T. Ozmen, Dünya borsalarında gözlemlenen anomaliler ve İstanbul Menkul Kıymetler Borsası üzerine bir deneme, Sermaye Piyasası Kurulu Yayını 61, Ankara, (1997).
[54] G. Muradoglu and T. Oktay, Türk hisse senedi piyasasında zayıf formda etkinlik: Takvim anomalileri, Hacettepe Üniversitesi İIBF Dergisi, 11, (1993), 51-62.
[55] M. B. Karan, The weekend effect in the Istanbul Stock Exchange market, Yaklasim, 20, (1994), 99-109.
[56] R. Bildik, Hisse senedi piyasalarında dönemsellikler ve İMKB üzerine ampirik bir çalışma, İMKB Yayınları, İstanbul, 2000.
[57] K. G. Metin, G. Muradoglu and B. Yazici, An analysis of the day of the week effect on the Istanbul Stock Exchange, BIST Review, 1, (1997), 15-25.
[58] C. B. Oguzsoy and S. Guven, Stock returns and the day-of-the-week effect in Istanbul Stock Exchange, Applied Economics, 35, (2003), 959-971.
[59] Inamlik, H. Berument and H. Kiymaz, Borsa değişkenliğinde haftanın gün etkisi, İktisat İşletme ve Finans Dergisi, 19(223), (2004), 91-102.
[60] M. Kiyilar and C. Karakas, İstanbul Menkul Kıymetler Borsasında zamana dayalı anomalilere yönelik bir inceleme, İ.Ü. İşletme İktisadl Enstitüsü Dergisi-Yönetim, 16(52), (2005), 17-25.
[61] K. Tuncel, İMKB'de haftanın günü etkisi, Akdeniz Üniversitesi İİBF Dergisi, 13, (2007), 252-265.
[62] M. F. Dicle and M. K. Hassan, Day of the week effect in Istanbul Stock Exchange, Scientific Journal of Administrative Development, 5, (2007), 53-83.
[63] H. Aktas and M. Kozanoglu, Haftanın günleri etkisinin İstanbul Menkul Kıymetler Borsası'nda GARCH modeli ile test edilmesi, Finans Politik \& Ekonomik Yorumlar Dergisi, 44(514), (2007), 37-45.
[64] R. Demirer and M. B. Karan, An investigation of the day-of-the-week effect on stock returns in Turkey, Emerging Markets Finance and Trade, 38(6), (2002), 47-77.
[65] Y. Yalcin and E. M. Yucel, Day-of-the-week effect on stock-market volatility and return: Evidence from emerging markets, Finance a úvûr-Czech Journal of Economics and Finance, 56(5-6), (2006), 258-279.
[66] T. Atakan, İstanbul Menkul Kıymetler Borsası'nda haftanın günü etkisi ve Ocak ayı anomalilerinin ARCH-GARCH modelleri ile test edilmesi, İstanbul Üniversitesi İşletme Fakültesi Dergisi, 37(2), (2008), 98-110.
[67] M. Aksoy and I. Dastan, Short selling and the day of the week effect for Istanbul Stock Exchange, International Research Journal of Finance and Economics, 70, (2011), 205-216.
[68] U. Basdas, The day-of-the-week effect for Istanbul Stock Exchange: A stochastic dominance approach, Journal of Applied Finance \& Banking, 1(4), (2011), 223-238.
[69] D. B. Nelson, Conditional heteroscedasticity in asset returns: A new approach, Econometrica, 59, (1991), 347-370.
[70] R. F. Engle, Autoregressive conditional heteroskedasticity with estimates of the variance of the United Kingdom inflation, Econometrica, 50, (1982), 987-1008.
[71] T. Bollerslev, A generalized autoregressive conditional heteroscedasticity, Journal of Econometrics, 31, (1986), 307-327.
[72] R. Connoly, An examination of the robustness of the weekend effect, Journal of Financial and Quantitative Analysis, 24, (1989), 133-69.
[73] F. Black, Studies of stock market volatility changes, Proceedings of the American Statistical Association, Business and Economic Statistics Section, (1976), 177-181.
[74] L. R. Glosten, R. Jagannathan and D. Runkle, On the relation between the expected value and the volatility of the normal excess return on stocks, Journal of Finance, 48, (1993), 1779-1801.
[75] C. Brooks and S. P. Burke, Information criteria for GARCH model selection: An application to high frequency data, European Journal of Finance, 9(6), (2003), 557580.
[76] T. Bollerslev, Ray Y. Chou and Kenneth F. Kroner, ARCH modeling in finance: a review of the theory and empirical evidence, Journal of Econometrics, 52(1-2), (1992), 5-59.
[77] T. Bollerslev and J. M. Wooldridge, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, Econometric Reviews, 1, (1992), 143-173.
[78] D. A. Dickey and W. A. Fuller, Distribution of the estimators for autoregressive time series with a unit root, Journal of the American Statistical Association, 74, (1979), 427-431.
[79] P. C. B. Phillips and P. Perron, Testing for a unit root in time series regression, Biometrika, 75, (1988), 335-346.
[80] G. Ljung and G. Box, On a measure of lack of fit in time series models, Biometrika, 66, (1979), 265-270.
[81] L. Harris, A transaction data study of weekly and intradaily patterns in stock returns, Journal of Financial Economics, 16, (1986), 99-117.
[82] J. Lakonishok and E. Marberly, The weekend effect: Trading patterns of individual and institutional investors, Journal of Finance, 45, (1990), 231-243.
[83] R. A. DeFusco, G. McCabe and K. C. Yook, Day of the week effect: A test of the information timing hypothesis, Journal of Business Finance and Accounting, 20(6), (1993), 835-842.
[84] N. Al-Loughani and D. Chappell, Modeling the day-of-the-week effect in the Kuwait Stock Exchange: A nonlinear GARCH representation, Applied Financial Economics, 11(4), (2001), 353-359.
[85] D. Tonchev and T. H. Kim, Calendar effects in Eastern European financial markets: Evidence from Czech Republic, Slovakia and Slovenia, Applied Financial Economics, 14, (2004), 1035-1043.
[86] L. Ederington and J. H. Lee, How markets process information: News releases and volatility, Journal of Finance, 48, (1993), 1161-1192.
[87] S. Mehdian and Mark J. Perry, The reversal of the Monday effect: New evidence from US equity markets, Journal of Business Finance and Accounting, 28(7-8), (2001), 1043-1065.
[88] Eugene F. Fama, The behaviour of stock market prices, Journal of Business, 38(1), (1965), 34-105.
[89] M. Gultekin and N. B. Gultekin, Stock market seasonality: International evidence, Journal of Financial Economics, 12(4), (1983), 469-481.
[90] T. Bollerslev, A conditionally heteroskedastic time series for speculative prices and rates of return, Review of Economics and Statistics, 69, (1987), 542-547.
[91] M. S. Beine, S. Laurent and C. Lecourt, Accounting for conditional leptokurtosis and closing days effects in FIGARCH models of daily exchange rates, Applied Financial Economics, 12, (2002), 589-601.
[92] R. Harris, C. Kucukozmen and F. Yilmaz, Skewness in the conditional distribution of daily equity returns, Applied Financial Economics, 14, (2004), 195-202.


[^0]:    ${ }^{1}$ Assoc. Prof. Dr., Dumlupınar University, Faculty of Economics and Administrative Sciences, Departmant of Economics, Kütahya/Turkey.

[^1]:    ${ }^{6}$ See, [90], [91], and [92], among the others.

