Durham University Business School

MSc Finance (Accounting and Finance)

St. Aidan's College

Dissertation Title:

Calendar Effects on Stock Returns in Turkish Stock Market

Submitted by Merve Yumusak

9/9/2014

Declaration

This dissertation is the result of my own work. Material from the published or unpublished work of others, which is referred to in the dissertation, is credited to the author in question in the text. The dissertation is approximately **9150** words in length.

Acknowledgment

Foremost, to Turkish Petroleum Corporation (TPAO), which is my guarantor company, many thanks for providing me this invaluable opportunity to study in Durham University.

I would like to thank my advisor Prof. Nigar Hashimzade for helpful comments.

To my sister, Gunay Aleskerli, who was always with me day and night and who supported me for the entire year. I owe many things to you. Moreover, to Charu Kanwar, who gives me great energy with her smile and friendship, loves to you.

To my fiancé, Basar Basaran, who has great patience in this long process away from home. Thank you for all of your love, support, help, encouragement and dedication.
Seni cok seviyorum.

To my family, who have always supported me. Thank you for your love. Cok tesekkur ederim, iyi ki varsiniz annem, babam ve abilerim.

Abstract

This study aims to investigate calendar anomalies in the Turkish stock market. The availability of the day of the week effect, January effect, and Turn of the month effect in the Borsa Istanbul BIST 100 Index are specially tested by using OLS, as well as GARCH type estimation methods. Contrary to previous findings, results indicate no significant the day of the week effect and January effect in the BIST 100 Index for the period of January 2005 – April 2014. However, the results show the evidence that the Turn of the month effect exists in the Turkish stock market.

Keywords: Market Efficiency – Market Anomalies, Return and volatility, the Turkish stock market, Borsa Istanbul, BIST, Istanbul Stock Exchange, Day of the week effect, Start of the week, January Effect, Turn of the month effect, OLS, GARCH models

Executive Summary

The purpose of the study is to investigate the existence of calendar effects on stock returns in the Turkish stock market. Borsa Istanbul BIST 100 (previously known as Istanbul Stock Exchange ISE 100) index is chosen to represent the features of the stock market returns. Among various calendar effects, most common anomalies, the day of the week effect, the January effect, and the Turn of the month effect are estimated.

Although estimation results have failed to add a supportive evidence for the day of the week effect and the January effect in the Turkish stock market, there is strong evidence for the Turn of the month effect on stock returns.

Further investigations into the Turkish stock market with different methodologies and different stock indices for another time periods have been cited as a potential source for future research.

To sum up, this study makes a contribution to stock market literature in several key ways. Primarily, the study presents alternative methodologies to test calendar anomalies for an emerging market. In addition, it includes recent data to show the effects of recent changes in the Turkish stock market in case of seasonality in stock returns. The results of this empirical study may be helpful for investors to develop trading strategies and investment decisions.

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Chapter I. Introduction

Calendar effects can be defined roughly as the systematic anomalies in financial asset returns at specific days, weeks, months or years (Brooks, 2008, p. 454). Even positions of the Sun, the Earth, and the Moon can be related to market anomalies (Taylor, 2005, p. 59). Calendar anomalies contradict with Efficient Market Hypothesis (EMH), which is one of the traditional finance assumptions because an investor can gain abnormal returns by developing trading strategies based on predicting systematic patterns of buying and selling stocks within a certain time (Demirer & Karan, 2002, p. 3).

According to EMH, asset prices fully reflect all available information and react promptly to new information when it is announced (Fama, 1991, p. 1575). It means stock prices reflect information about their fundamental values. Key features of EMH are rational expectations of individuals and random walk of asset prices. Rational behaviour is to maximize utility given budget constraint of individuals. Even in case of irrationality, stock trading continues happening randomly, stock returns will cancel each other, so irrationality do not have impact on prices (Shleifer, 2000). Thus, random walk is also essential idea of EMH. New information is unpredictable. Thus, differences in price changes should be random and uncertain in an efficient market (Forbes, 2009).

On the contrary, however, behavioural finance supporters suggest that these features may not be observed in financial markets, and these variations from EMH are called as market anomalies. Anomalies can be categorized as calendar, fundamental, technical, economical based, and political based market anomalies (Buyuksalvarci, 2009, p. 109; Al-Jafari, 2012, p. 141). One of the significant market anomalies is calendar anomalies that explain different behaviours of equity on a different days, months or years. Some examples of calendar anomalies are daily anomalies, January effects, and turn of the month effects, which will be examined in this paper.

"This time it is different." [1]

The slogan used by 2014 European Parliament Elections could also be adapted for investors in stock markets. This paper attempts to ask these questions: "Is it indeed different to gain from stock returns in this particular time?", "Can investors find patterns coinciding with certain calendar time to make profitable investments by developing strategies accordingly?" Therefore, this study aims to contribute the literature by analysing calendar effects in an emerging equity market, the Turkish stock market by using its stock index BIST 100 with recent dataset. The data consists of the BIST 100 Index returns calculated from daily closing prices for the period between 01.01.2005 and 30.04.2014. Daily stock market returns are elucidated for market anomalies with linear and non-linear estimation methods in the Turkish stock market. Eviews7 is used for regression analysis.

Paper Structure

Chapter 1 has mentioned the primary goal and context of the study and broad explanations for stock market efficiency and market anomalies. The structure of the study will continue as follows. Chapter 2 will present literature review for calendar anomalies and general features of Borsa Istanbul. Chapter 3 will include data sample and introduce the methodologies and hypotheses of the study. Empirical findings from regression analysis will be presented within Chapter 4.Chapter five will consist of concluding remarks. The study will be ended with the concluding remarks as well as constraints of the study and opportunities for further research.

[1] Information extracted from the website: http://www.elections2014.eu/en/news-room/content/20140210IPR35560/html/The-2014-European-elections-this-time-it's-different

Chapter II. Literature Review

The chapter aims to present a relative literature review for calendar anomalies. For this reason, firstly, market efficiency and market anomalies will be mentioned. Then, secondly, calendar effects, which are market anomalies, especially the day of the week effect, the January effect, and the turn of the month effect, will be discussed. Notably, the papers on the Turkish stock market will be focused. The final part will contain the feature details of Borsa Istanbul Equity Market.

2.1. Market Efficiency and Market Anomalies

What is an efficient market?

Fama (1969, p. 383) called a market as efficient if prices fully reflect all existing information. Financial efficiency of the stock markets is determined by three fundamental criteria; allocative efficiency (optimal allocation of stocks), operational efficiency (transferring stocks at minimum cost), and informational efficiency (reflecting all available information by stock prices) (Buyuksalvarci, 2009, p. 108).

Fama (1969) proposed Efficient Market Hypothesis (EMH) to evaluate informational efficiency of the stock market and to explain dynamics that influence the formation of equity prices. EMH with traditional finance assumptions suggest that asset prices should follow a random walk. That makes prices unpredictable (Brooks, 2008, p. 326).

Fama (1991) classified informational efficiency of markets as weak form efficient, semi-strong form efficient and strong form efficient. Weak form efficient implies that all information is only historical prices. Semi-strong form efficient requires that prices reflect historical prices as well as publicly available information. Strong form efficient means that some group of investors have private information which affects the formation of prices.

Recent studies of market efficiency on Borsa Istanbul have attempted to test weak-form efficiency or semi-strong form efficiency of the Turkish stock market (Duman Atan, et al., 2009, p. 36).

What is a market anomaly?

If investors can earn abnormal returns by developing strategies based on past information, this situation is against to the EMH, and it is called as market anomaly. Size effect and calendar effects as the most common market anomalies are extensively documented in the literature.

Anomalies may indicate market inefficiency or an inappropriate asset pricing model (Bildik, 2004) or different risk premiums at different times (Kohers, et al., 2004, p. 167). If price movements, that are not consistent with EMH, are observed in financial markets, it can be concluded that markets are not efficient.

2.2. Calendar Effects

Wide-ranging literature on calendar anomalies is available. First studies have been made in US stock markets. Later, studies on international equity markets also have been carried out. There have been numerous studies of calendar effects on not only stock market returns and volatility but also Real Estate Investment Trusts (REIT) returns, Derivatives Exchange returns and returns of precious metals equity, such as gold and silver for evidence of seasonality (Aksoy, 2013, p. 151).

Several empirical findings show that the availability of calendar effects cannot be ignored (Brooks, 2008, p. 455). Calendar effects include the January effect, the day of the week effect, the turn of the month effect, the holiday effect, the turn of the year effect, moon phase effect, the school-out effect (Coakley, et al., 2012), the holy days effect (the Muslim feast of Ramadan and Eid (Oguzsoy & Guven, 2003)), and the Chinese (Lunar) New Year effect (Wong, et al., 1990).

It is recently documented that some calendar anomalies are disappearing. Rubinstein (2001), Sullivian, et al. (2001) for the period of 1973-1996, Schwert (2001) are the first research suggested that Monday effect tends to disappear (Bildik, 2004, p. 2). Maberly & Waggoner (2000) shows that the turn of the month effect started to become vanished. However, when much longer periods are covered, calendar anomalies can still be observed in equity markets (Taylor, 2005, p. 59). For example, Lakonishok & Smith (1988) covered ninety years period to illustrate calendar effects.

The day of the week effect and the January effect are the most commonly studied calendar effects (Thusara & Perera, 2014). In addition to these anomalies, turn of the month effect will be examined in the following sections in detail.

2.2.1. Day of the week effect

The day of the week effect leads to anomalies in average returns on certain days of the week than other days (Brooks, 2008, p. 454). In the literature on calendar effects, 'the day of the week effect' or 'Monday effect' or 'weekend effect' is described as the negative stock returns calculated from the close price on Friday to the close price on Monday. Monday returns are the return from the three-calendar-day investment, while returns of other days are just coming from the one-calendar day investment French (1980, p. 56). Taylor (2005, p. 60) states that Monday, which is the first day of trading week days, has negative average return between -0,2% and -0,1%.

Empirical studies indicate some hypothesis that the day of the week effect on equity returns mainly stems from the settlement period, bid-ask spread biases, dividend procedures, information release hypothesis, measurement errors, thin trading, and investors' behaviour. (Ulussever, et al., 2011). According to the information release hypothesis, negative information about companies is likely to be released on Friday near to end of the session or at the weekend (Penman, 1987). Thus, demands for assets on Monday decrease as a result of bad news.

Another explanation for lower Monday returns is investors' behaviours. Individual investors are active on Monday according to Osborne (1962) and Lakonishok & Maberly (1990), because they have more time on weekends to think and to make financial decisions. Abraham & Ikenberry (1994) is also stated that investors tend to sell on Monday after evaluating their investments on weekend. Moreover, the settlement date can be used to explain the day of the week effect, if the settlement day and the trade day are not the same. For example, in case of the 2-day settlement date rule, investors can enjoy interest-free credit for 3 days if they buy stocks on Thursday because they do not need to pay in the same week (Berument & Dogan, 2012, p. 283).

Monday effect has also extensively seen in the volatility of stock returns. Studies indicate higher variance on Monday because weekend can add more variance Monday, which reflects the total news of three days (Taylor, 2005, p. 66).

First studies of the presence of the day of the week effect were conducted for US stock markets. In general, low Monday returns and positive Friday returns examined in US stock markets from 1897 until the 1980s (Taylor, 2005, p. 59). Osborne (1962) and Cross (1973) first mentioned Monday effect and studied stock returns to compare mean returns on different days and stated that average Monday return is negative and lower compared to other days. For the period of 1953-1970, Cross (1973) found that average returns of Fridays are higher than average returns on Mondays on S&P 500 Index. French (1980) also investigated that Monday returns are negative whereas returns of the rest of the days of a week are positive on the S&P 500 Index between the years 1953 - 1977. Gibbons & Hess (1981) further studied on these papers and confirmed the findings, as well as they argued that the difference in settlement periods does not explain the day of the week effect. Berument & Kiymaz (2011) investigated 25-years data for S&P Index from 1973 to 1997 and by using modified GARCH models, they found that highest return and the lowest variation are observed on Wednesday. Moreover, there are other studies, e.g. Lakonishok & Smidt, (1988), for the day of the week Jones Industrial Index, indicating statistically significant negative returns on Monday.

Besides studies on the US stock market, several international studies of the day of the week effect are available. Agrawal & Tandon (1994) found daily anomalies in eighteen countries' stock markets. However, Kohers et al.(2004) documented that the day of the week effect is disappearing in several developed countries. Bashera & Sadorskya (2006) studied on twenty-one developing countries for the period of 1992-2003, found no evidence of daily anomalies for most of the countries.

Calendar effects in Europe have become significant after 1985 according to Taylor (2005, p. 61). Apolinario, et al. (2006) studied on European stock markets and documented that the day of the week effect do not exist in most of the European equity markets (Güler & Çimen, 2014).

Wong et al.(1992) documented the day of the week effect for the period of 1975 - 1988 in five Asian countries. It is stated that four countries have positive Friday returns, and negative Monday returns are observed in Singapore, Malaysia, and Hong Kong. Al-Jafari (2012) carried out a research on the day of the week effect on the Muscat security market and found no significant evidence for the day of the week effect with GARCH (1,1), TGARCH (1,1), and EGARCH (1,1) methodologies.

Turkey

Several studies do suggest that the day of the week effect is also available in the Turkish stock market. Balaban (1995) found evidence for the day of the week effect in the period of 1988-1994 by using the Istanbul Securities Exchange Composite Index (ISECI). According to Balaban (1995), the Tuesday return is the lowest but insignificant, Friday return is significant and the highest.

Bildik (2004) also studied on the Istanbul Stock Exchange 100 Index (ISE 100) for the data between 1988 and 1999, documented the existence of calendar anomalies. He suggests that Tuesday is insignificant and the lowest, Thursday is significant and the highest return because of the two-day settlement period after 1994.

Demirer & Karan (2002) found complementary evidence for the day of the week effect, greater Friday returns from 1986 to 1996. They also documented that the lag return is significant so start of the week effect is important.

Oguzsoy & Guven (2003) used ISE 100 Index as well as ISE 30 companies and stated the existence of the day of the week effect, Tuesday has the lowest return, and Friday has the highest return for the period of 1988-1999.

Inamlik, et al., (2004) investigated the period of 1986-2003 by estimating a GARCH model to show the day of the week effect on stock returns and volatility. They documented statistically significant evidence that Monday has the lowest return and the highest volatility, Friday has the highest return and Tuesday has the lowest volatility.

In addition to the findings of Inamlik, et al., (2004); Balaban (1995), Oguzsoy & Guven (2003), and Bildik (2004) have documented highest variance on Monday. Contrary to these findings Cicek (2013) reported the lowest volatility on Monday with a recent data set.

Tuncel (2008) documented no significant differences among daily returns, but found some proofs for the day of the week effect in the Turkish stock market by using three years data from 2005 to 2007.

Dicle & Hassan (2007) used ARCH-GARCH model for a longer period from 1987 to 2005 and found that Monday has a negative return; Thursday and Friday have positive returns. Aktas & Kozoglu (2007) investigated the day of the week effect via GARCH (1,1) and GARCH (1,1)-M models and found significant Thursday and Friday returns on different Borsa Istanbul Indices from 2001 to 2007.

Atakan (2008) documented the day of the week effect for twenty years (1987-2008) by estimating a GARCH model and found statistically significant higher and positive Friday returns and lower and negative Monday returns. For the same time period data set, Atakan (2009) also suggested that the most appropriate methodology for ISE 100 index is standard GARCH (1,1) because of the presence of the ARCH effect.

Cicek (2013) has recently studied different BIST stock indices over the period 2008 and 2012. According to EGARCH (1,1) estimation results, she found that positive and significant Monday returns, positive but not significant Friday returns. Moreover, volatility is significant and lower on Mondays and higher on Fridays for the BIST 100 Index.

There are hypotheses to attempt to explain the day of the week effect. Examples of the hypotheses are cost of daily cash transitions and settlement period (Gibbons & Hess, 1981). Bildik (2004) examined the Turkish stock market returns by separating periods according to settlement day. The settlement date of Borsa Istanbul has increased from one day to two days at 29 July 1994 (Oguzsoy & Guven, 2003, p.963). After the settlement day was increased from one day to two days, stock returns on Thursday became higher, previously Friday returns were higher. Buyers on Thursday can enjoy interest-free credit for extra 2 days over the weekend because they do not need to pay until Monday. However, Jaffe & Westerfield (1985) showed that the settlement period hypothesis was not hold. Many countries have similarly influenced from the day of the week effects although they have different settlement periods (Wang, et al., 2013, p. 70).

Jaffe and Westerfield (1989) tested the daily irregularity in a different way in another study. They studied on changes in signs of returns rather than absolute values. They found that returns from Friday to Monday shows a transition from negative to positive.

-Start of the Week Effect

Demirer & Karan (2000) mentioned that there is another daily anomaly which is Monday returns may affect the rest of the week returns. Start of the week effect means that average daily returns can vary according to the return of Monday. They found that if Monday return is positive, the mean return for the whole week is also likely to be positive.

Table 1 presents several academic papers on calendar anomalies in the Turkish stock market. Most of the papers have used ISE 100 (BIST 100) Index to explore calendar effects. This tendency leads this study to choose the BIST 100 Index as a representative for the Turkish stock market.

Table 1: Examples of articles for calendar anomalies in the Turkish stock market

Paper	Period	#*	Methodology	Index
Balaban (1995)	1988-1994	8	OLS	ISECI
Bildik (2004)	1988-1999	10	OLS F-tests, KW tests	ISE100
Karan (2001)	1991-1998	8	OLS test, t-test	ISE100
Demirer & Karan (2002)	1988-1996	19	OLS	ISE
Oguzsoy & Guven (2003)	1988-1999	22	OLS	ISE30,ISE100
Inamlik et al. (2004)	1986-2003	17	Statistical test	ISE100
Aktas & Kozoglu (2007)	2001-2007	6	GARCH, GARCH-M	mix ISE indices
Atakan (2008)	1987-2008	21	ARCH-GARCH	ISE100
Eken & Uner (2008)	1988-2007	20	Statistical test	ISE100
Cinko (2008)	1989-2006	18	Statistical test	ISE100
Tuncel (2008)	2005-2007	3	OLS	ISE100
Basdas (2011)	1988-2010	23	Stochastic Dominance	ISE100
Kamath & Liu (2008)	2003-2007	5	OLS & GARCH	ISE100
Abdioglu & Degirmenci (2013)	2003-2012	10	OLS	ISE100
Cicek (2013)	2008-2012	5	EGARCH (1,1)	mix ISE indices

* The column '#' indicates the number of years of the data.

2.2.2. January effect

The January effect means that in January equity returns are higher than the other months. Two hypotheses are proposed to explain this anomaly. First, ‘tax-loss selling’ hypothesis for the tax year ending in December, companies sell their stocks in December and buy them in January (Reinganum, 1983). Second, performance evaluation of portfolio managers can also be regarded as an explanation of January effect (Kucuksille, 2012, p. 130). Rozeff & Kinney (1976) documented that US stock returns are higher in a new tax year, January. Before 1917, there was no need to sell assets for tax reasons, thus, there was no January effect before that year (Schults, 1985 cited in (Taylor, 2005, p. 64). Gultekin & Gultekin (1983) showed the January effect for 13 countries out of 17 countries for the period of 1959-1979. Basher and Sadorsky (2006) argued that in general the January effect is not available in emerging markets.

For Turkey, Kucuksille (2012) found the January effect in different indexes including the BIST 100 Index for the period of 1988-2010. Karan & Uygur (2001) also documented this effect that is related to the size of the company for the period of 1991 through 1998. Moreover, Bildik (2004, p. 11) found that the mean stock return in January is statistically higher over the year. Contrary to these findings, Atakan (2008), Cinko (2008), Tuncel (2012) reported that any variances in January stock returns in the Turkish stock market were not available for periods of 1987-2008, 1989-2006, and 2000-2010, respectively. The different results can be the outcome of applying different estimation methods, and using different time periods. Whereas Kucuksille (2012) by using the power ratio method developed by Gu (2003); Atakan (2008) used a GARCH model and Cinko (2008) used non-parametric model Mann-Whitney U test to detect January effect.

2.2.3. Turn of the month effect

The turn of the month effect is one of the market anomalies that indicate abnormal returns at the beginning and end of the month. Ariel (1987) was the first to document this irregularity that positive returns are observed in the first half of the month. From the final day of the previous month to the first four day in the current month, the average gain is higher than the average return of the rest of the month.

Lakonishok & Smidt (1988) investigated the turn of the month seasonality for the DJIA DOW Jones index. They found the last day of the previous month and the first three day of the current month (four days) have significantly very high returns for the period from 1897 to 1986. Maberly and Waggoner (2000) argued that the turn of the month effect for S&P 500 futures disappeared after 1990.

There are studies on the turn of the month effect in the Turkish stock market as well. Guler & Cimen (2014) has recently compared five emerging markets with the Borsa Istanbul equity market for the day of the month anomaly. They found that the turn of the month effect exists for the BIST 100 Index for the period of 1988-2012. Akyol (2006) found the existence of the turn of the month effect in the ISE 100 Index for the years 1987-2006 (Basdas, 2011, p. 226). Hepsen (2012) also discovered significant results for the turn of the month effect in the ISE REIT[2] market over the period 2000-2010.

One of the possible reasons for the turn of the month effect suggested by Penman (1987) is that the tendency of companies to announce good news in the first half of the month. Another hypothesis of the turn of the month effect was proposed by Ogden (1990) suggesting that the turn of the month may be the result of standardization in cash flows and payment systems (Bildik, 2004, p. 5) .

[2] Istanbul Stock Exchange Real Estate Investment Trusts

Abdioglu & Degirmenci (2013, p. 69) considered the fifteenth of each month as a turn of the month because public sector makes salary payments at the middle of the month in Turkey. They indicated that there is no availability of the turn of the month effect in the BIST 100 Index for the years between 2003 and 2012.

2.3. Borsa Istanbul

This study will carry out the empirical study of the Turkish stock market. The Turkish stock market is emerging stock market, and it is continuously developing by having technological and international agreements, e.g. partnership with NASDAQ OMX Group in 12/2013[3]. The name of the stock market is currently Borsa Istanbul Equity Market (BIST). Previously, it was called as Istanbul Stock Exchange (ISE). Borsa Istanbul started trading at 3 January 1986. Operation time is 9:30-12:00 and 14:00 - 16:30 with 2 sessions from Monday to Friday. In the times of the Ottoman Empire, a security market was also available, which is dated back 1866. The Turkish stock market was fully computerized in 1994. BIST 100 which was first introduced in 1995 is computed as free float market capitalization weighted[4].

This study focuses on the investigation of calendar effects on the Turkish stock market with current data covering recent developments in Borsa Istanbul Equity Market.

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[3] http://borsaistanbul.com/en/news/2013/12/31/nasdaq-omx-and-borsa-istanbul-sign-landmark-deal and http://www.nasdaqomx.com/

[4] BIST 100 index is working as the main index for Borsa Istanbul Equity Market. It includes a hundred stocks selected among the stocks of companies which are traded on the National Market and the stocks of REIT and VCIT traded on the Collective Products Market. BIST 100 index automatically involve BIST 30 and BIST 50 stocks. The information is extracted from http://borsaistanbul.com/docs/default-source/endeksler/bist-stock-indices-ground-rules.pdf?sfvrsn=6

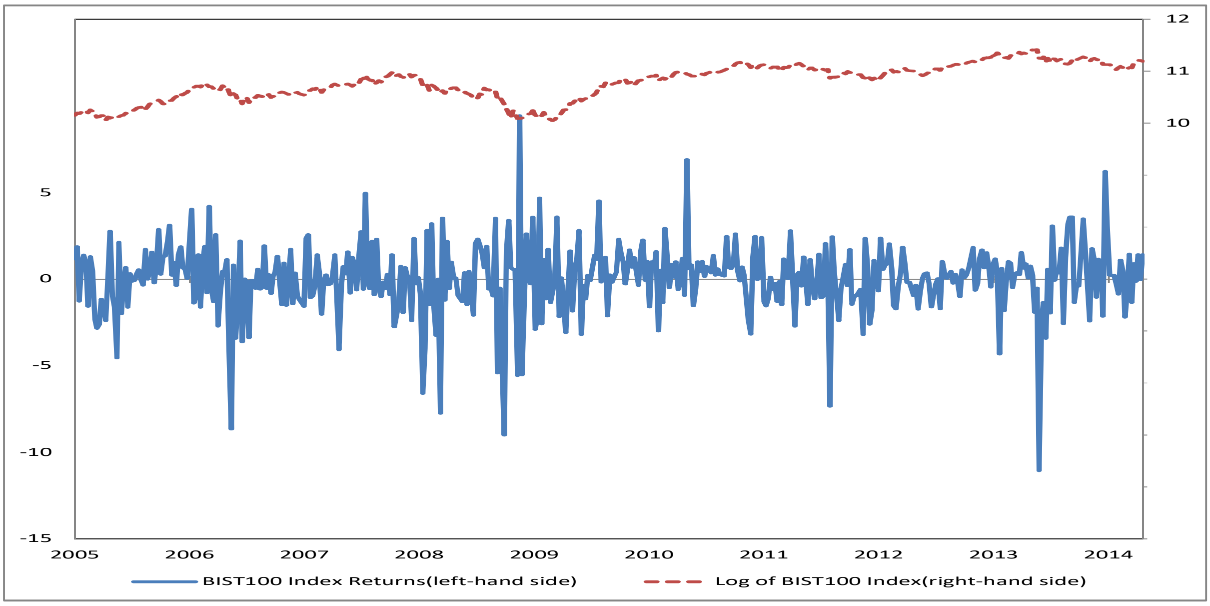
Chapter III. Data and Methodology

The main purpose of the Chapter three is to describe the dataset and to introduce the methodologies using for the empirical findings. Firstly, general features of data set will be explained. Secondly, the calculation method of stock returns and correlogram of returns will be presented. Third, details for descriptive statistics of daily returns will be given. Then, unit root tests will be applied to the time series in log levels as well as to the return series. Finally, estimation methods for research questions will be explained in detail.

3.1. Data Set

Daily close-to-close price index XU100 - BIST 100 data is obtained from Borsa Istanbul website[5]. Between 01.01.2005 and 30.04.2014 days are covered. The data consists of 2328 daily observations of the BIST 100 Index (See Table 2). Eviews7 statistics tool is used for the estimation of the data. Figure1 illustrates the graphs of the return of price index and the log level of price index from 2005 to 2014. The graph of daily returns shows fluctuations, while the log of price graph (dashed line) exhibits slight changes and eventually has an increasing trend.

Figure 1: BIST 100 Price index Return and the log of price index 2005-2014



[5] Information extracted from http://www.borsaistanbul.com/en/data/data/index-data

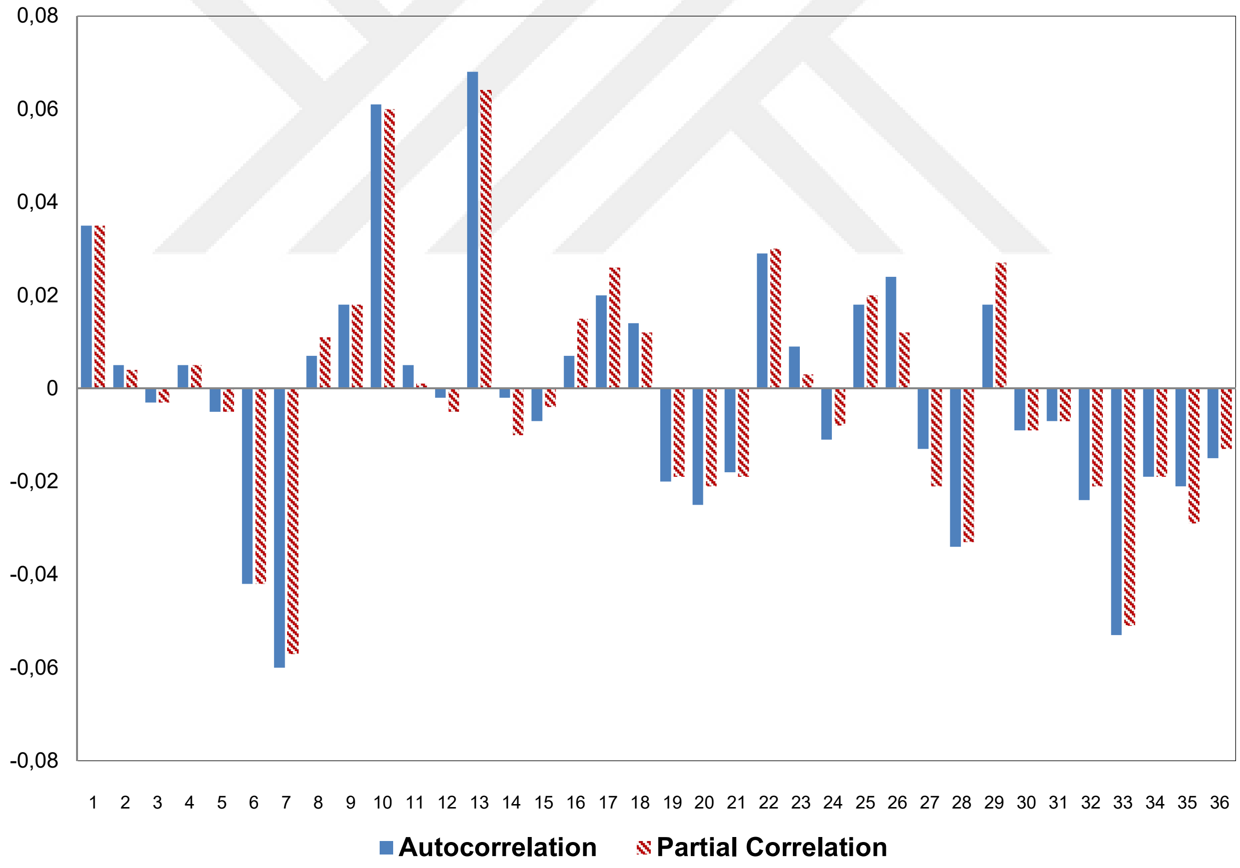
3.2. Stock Returns

Market return is the changes in the log level of prices (Taylor, 2005, p. 15). Daily returns are calculated by using closing index values with the following formula;

$$R_t\% = dlog\ (\text{ the BIST 100 Index closing price})^*\ 100 = [log\ (I_t) - log\ (I_{t-1})]^*100$$

Where I_t is the Borsa Istanbul 100 Index for the day t, R_t is the return on the BIST 100 Index for day t. First differenced logarithm of price index is multiplied by hundred to have percentage values. Figure 2 shows the correlogram of the BIST 100 Index return series for 36 lags. According to ACF and PACF graphs, serial correlation exists; especially, it is visible that Lag 1 is significant.

Figure 2: Correlogram for return series the BIST 100 Index 2005:2014



3.3. Descriptive Statistics on Return Series

Below Table 2 illustrates the descriptive statistics for the return series day of the week accordingly. Each column shows the statistical features of each trading day. The last column reflects the characteristics of all trading days.

Table 2: **Descriptive Statistics of the return series the BIST 100 Index – 2005-2014**

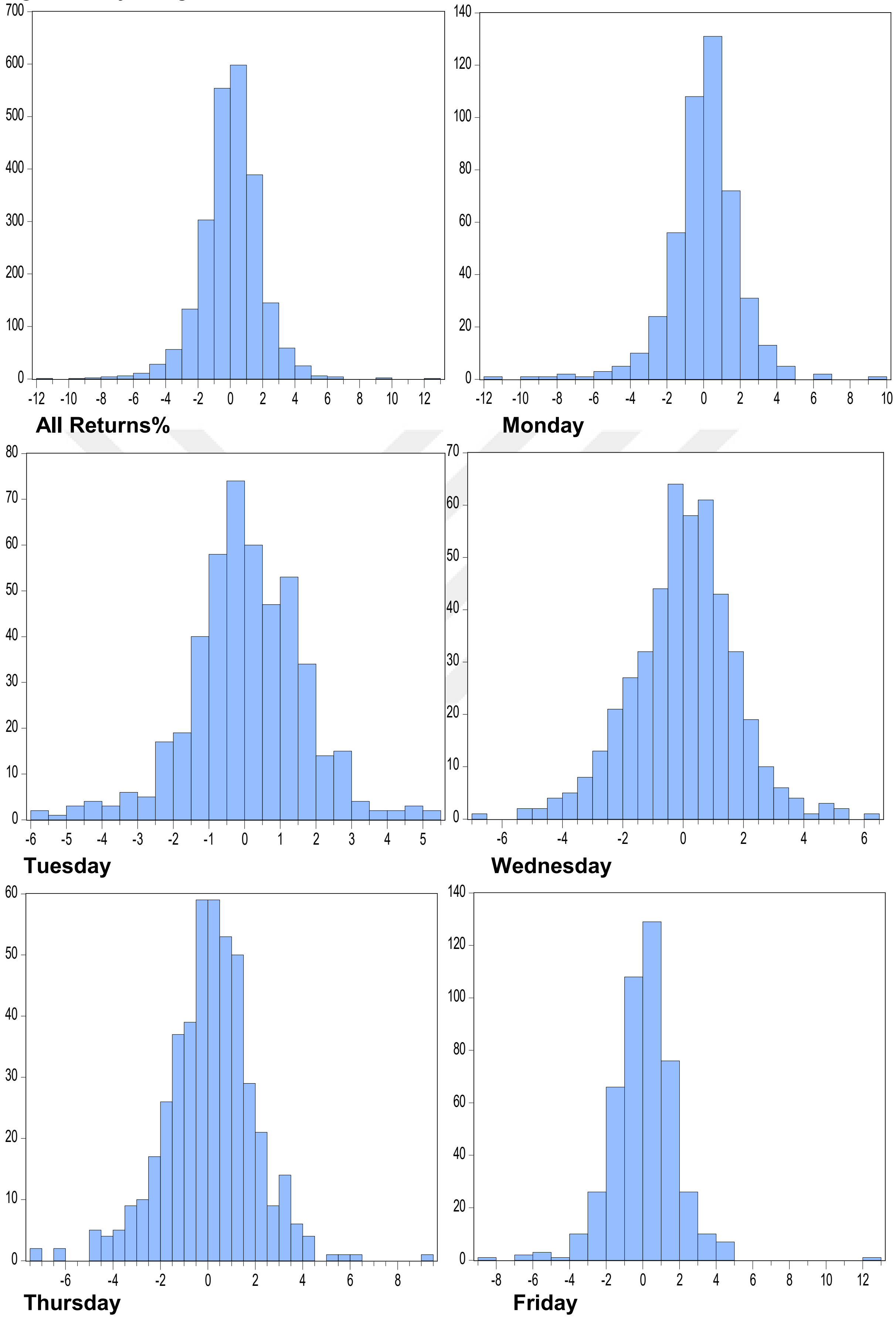
	Monday	Tuesday	Wednesday	Thursday	Friday	All Days
Observations	467	468	463	464	466	2328
Mean	0.04	0.05	0.01	0.07	0.06	0.05
Std.Devn.	1.97	1.63	1.74	1.93	1.78	1.81
Skewness	-0.79	-0.21	-0.14	-0.14	0.18	-0.26
Kurtosis	5.50	1.28	1.09	1.99	5.77	3.52
Minimum	-11.06	-5.84	-6.90	-7.06	-8.03	-11.06
Maximum	9.43	5.29	6.48	9.39	12.13	12.13
Asymptotic test: Chi^2(2)	635.69 **	35.42 **	24.44 **	78.35 **	648.56 **	1229.10 **
Normality test: Chi^2(2)	149.34 **	25.50 **	20.00 **	52.53 **	247.37 **	542.04 **

In Table 2, the first row is providing the number of observations for each day of the week. The number of observations is not equal for each day. The second row indicates the daily mean returns. For all days of the week, average stock returns are positive. The highest mean return is on Thursday, with the value of 0.07. The minimum return is seen at on Monday -11.06, maximum return is on Friday, -12.13.

Skewness values of all days are negative, except Friday. This accounts for the asymmetric response to negative shocks and long left tails distribution of the series, excluding Friday. High kurtosis, leptokurtosis 3.52 is observed in whole dataset. Negatively skewed, and fat tail data indicates non-normal return distributions. In the last row, the results of Normality test also rejects the null hypothesis of the return series are normally distributed.

The highest standard variance is on Monday, 1.97. This means the BIST 100 Index is more volatile on Mondays, Thursdays, and Fridays. Figure 3 is helpful to examine the differences in mean returns and standard deviations across the days. More dispersion of returns on Mondays (horizontal axis values from -12 to 10) can be seen by examining Figure 3 for each day histograms separately.

Figure 3: Daily Histograms of the BIST 100 Index Return series 2005:2014



3.4. Stationarity and Unit Root Testing

This part will present tests for non-stationarity in BIST 100 Price Index. Stationarity condition is one of the essential concepts for time series because it has effects on features of the time series (Brooks, 2008, p. 207). To test the availability of unit root, first augmented Dickey-Fuller ADF (Dickey & Fuller, 1979) test applied and compared with KPSS (Kwiatkowski, et al., 1992) test to robust the ADF test results. ADF tests are employed with three alternatives, which are without intercept, with intercept, and with trend & intercept. The results are illustrated separately on the Table 3 and Table 4.

Table 3 shows the results of ADF test on the log level of the BIST 100 price index. ADF test statistics is lower than critical values. Thus, the test results are not significant. The null hypothesis of non-stationarity cannot be rejected. The BIST 100 Index is non-stationary in their log levels, so time series should be first-differenced to turn into stationary.

Table 3: **ADF test for Log of the BIST 100 Index Series**

	Without intercept	**With intercept**	**With Trend& Intercept**
ADF test statistic	1.1642	-1.6800	-2.2482
Probability	0.9376	0.4414	0.4618
1% critical value	-2.5659	-3.4329	-3.9619
5% critical value	-1.9409	-2.8625	-3.4117
10% critical value	-1.6166	-2.5673	-3.1277
MacKinnon (1996) one-sided p-values			
Lag Length: 0 (Automatic - based on SIC, maxlag=36)			

H_0: RETURN has a unit root, it is not stationary,

H_1: RETURN does not have a unit root.

Table 4: **ADF Test for the BIST 100 Index Return Series**

	Without intercept	**With intercept**	**With Trend& Intercept**
ADF test statistic	-46.5437***	-46.563***	-46.557***
Probability	0.0001	0.0001	0.0000
1% critical value	-2.5659	-3.4329	-3.9619
5% critical value	-1.9409	-2.8625	-3.4117
10% critical value	-1.6166	-2.5673	-3.1277
MacKinnon (1996) one-sided p-values			
Lag Length: 0 (Automatic - based on SIC, maxlag=36)			

ADF test is applied to return time series that are integrated of order 0; I(0) and the results are displayed on Table 4. According to unit root test results, test statistics is higher than 1%, 5%, 10% critical values. The null hypothesis of the non-stationarity of return series can be rejected with significant ADF test statistics results. It proves that stationarity is satisfied when the price index is first differenced.

In order to robust the results of ADF test, KPSS test statistics is also applied on return time series and results are demonstrated on Table 5. The null hypothesis of KPSS test is that the return is stationary.

Table 5: **KPSS test for the BIST 100 Index Return Series**

	Without intercept	**With Trend& Intercept**
ADF test statistic	0.065	0.055
1% critical value	0.739	0.216
5% critical value	0.463	0.146
10% critical value	0.347	0.119

According to KPSS test statistics, the null hypothesis of stationarity of return series cannot be rejected because the test statistics are lower than critical values at 1%, 5%, 10% levels. Thus, KPSS test result is in line with ADF test results.

All in all, the two unit root tests have rejected the null hypothesis of non-stationarity of time series. Moreover, unit root test results indicate that return series behave as random walks. This result supports the weak form inefficiency of the Turkish stock market.

3.5. Methodologies

OLS, GARCH (1,1), EGARCH (1,1), TGARCH (1,1) models will be employed with dummy variables regressions. Chen, et. al (2001) investigated that different estimation method and different period of study may affect the results of the day of the week anomaly in stock markets of China. That's why, in this study, calendar anomalies in the Turkish stock market will be tested with different estimation methods. Moreover, in order to examine different time periods, data will be divided as yearly data, the first five-year data, and the last five-year data.

3.5.1. OLS

The first estimation method is Ordinary Least Squares (OLS). Numerous studies in the literature have used this methodology to test the day of the week effect.

Firstly, following the regression estimates daily seasonality in BIST 100 returns.

$$R_t = c + \beta_1 D1 + \beta_2 D2 + \beta_3 D3 + \beta_4 D4 + \alpha R_{t-1} + \varepsilon_t \qquad [1]$$

Where R_t is the BIST 100 Index return on the day t. ε_t is the stochastic error term, which is independently, identically distributed (IID).

D1 is a dummy variable for Monday; *D2* is for Tuesday, *D3* for Wednesday, *D4* for Thursday. *D1* is taking the value one if the day is Monday, zero otherwise. The dummy variable for Friday is dropped in order to avoid multicollinearity. *c* is coefficient and gives an estimated value for Friday mean return. β_1 can be seen as the difference in average returns between Friday and Monday. The coefficient α is for the previous day return.

Secondly, below regression is used to estimate monthly seasonality in the BIST 100 Index.

$$R_t = c + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 + \beta_8 D_8 + \beta_9 D_9 + \beta_{10} D_{10} + \beta_{11} D_{11} + \varepsilon_t \qquad [2]$$

D_1 is a dummy variable for January, D_2 for February. D_3 for March, D_4 for April, D_5 for May, D_6 for June, D_7 for July, D_8 for August, D_9 for September, D_{10} for October, D_{11} for November. The dummy variable for December has omitted to eliminate possible multicollinearity. D_1 is one if the trading day belongs to the month of January, zero otherwise. β_1 stands for the difference in mean returns between December and January. c is constant and represents the average return in December. ε_t is the error term.

Thirdly, to test the turn of the month (TOM) effect, the regressions previously employed by Compton et al.(2013) are used in this study. There are two regressions to test the turn of the month effect. The first is to test the difference between average daily returns of eighteen days around turn of the month. D_t is the dummy variable that takes value of 1 if it is the first trading day of a month, 0 otherwise. ε_t is the error term.

$$R_t = \beta_{-9} D_{-9t} + \beta_{-8} D_{-8t} + \ldots + \beta_8 D_{8t} + \beta_9 D_{9t} + \varepsilon_t \qquad [3]$$

In order to identify the turn of the month effect in the BIST 100 Index, the last regression is comparing the difference between mean daily returns around the turn of the month and mean daily returns of the rest of the month.

$$R_t = c + \beta_1 D_{TOM} + \varepsilon_t \qquad [4]$$

c is constant indicating the average return for the rest of the month (ROM); D_{TOM} is dummy variable for the turn of the month; therefore, if the days are t-1, t, t+1, t+2, t+3, it takes the value one, zero otherwise. t is the first trading day of the month; t-1 is the final trading day of the previous month, t, t+1, t+2, t+3 are respectively the first four trading days of the current month.

Hypotheses

This research has tested below hypotheses by using t-statistics and F-statistics. If t-test statistics is not significant, the null hypotheses of no daily anomalies, no January effect, and no turn of the month effect cannot be rejected. If we cannot reject the null hypothesis, it means that calendar anomalies do not exist in the BIST 100 Index.

1. H_0= There is no difference among mean returns of weekdays.

   (β_1= β_2= β_3= β_4=0)

   H_1=At least one day has significantly different mean return from other days.
2. H_0= No January effect. Mean returns are expected to be equal for each month of a year.

   (β_1= β_2= β_3= β_4= β_5= β_6= β_7=β_8= β_9= β_{10}= β_{11}=0)

   H_1=average return of the month is significantly different from other months.
3. H_0= average daily returns are zero for 18 days around turn-of-the month.

   (β_{-9}= β_{-8}= … =β_8= β_9=0)

   H_1= average daily returns for 18 days are significantly different from zero.
4. H_0= average returns for turn-of-the month are expected to be equal to return for the rest of the month (β_1=0)

   H_1=average returns around turn of the month are different from the average return of the rest of the month.

After OLS regressions are tested, autocorrelation and ARCH effects will be tested. If there is strong evidence for those effects, GARCH models will be more appropriate to evaluate the data. For model checking following hypotheses are used.

H_0: There is no autocorrelation in residuals.

H_0: There is no autocorrelation in squared residuals.

H_0: There is no ARCH effect.

3.5.2. GARCH - type models

Besides OLS method, GARCH type models as alternative estimation methods will also be exhibited in this report. Bollerslev (1986) and Taylor (1986) developed a GARCH type model to express conditional variance (σ^2_t) that is dependent on its previous lags. The GARCH (1,1) model can be enough to illustrate the volatility clustering feature of this data. For the GARCH type models MLE (Maximum Likelihood Estimation) methodology will be used in Eviews.

$$R_t = c + \beta_1 D1 + \beta_2 D2 + \beta_3 D3 + \beta_4 D4 + \alpha R_{t-1} + \varepsilon_t , \quad \varepsilon_t / \varphi_{t-1} \sim N(0, \sigma_t) \qquad [5]$$

<u>conditional variance equations</u>

GARCH (1,1) $$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \beta\, \sigma^2_{t-1} \qquad [6]$$

EGARCH (1,1) $$log(\sigma^2_t) = \omega + \alpha \left(\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma^2_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma^2_{t-1}}} + \beta\, log(\sigma^2_{t-1}) \qquad [7]$$

TGARCH (1,1) $$\sigma^2_t = \omega + \alpha\, \varepsilon^2_{t-1} + \gamma \sigma^2_{t-1} I_{t-1} + \beta\, \sigma^2_{t-1} \qquad [8]$$

Equation 5 shows the mean return equations for the day of the week effect. Equation 6, 7, and 8 demonstrate conditional variance equations for GARCH type models separately. The Exponential GARCH (EGARCH) model proposed by Nelson (1991) can cope with non-negativity constraint and leverage effects. Researcher do not need to deal with negativity because conditional variance equation of EGARCH (1,1) is already positive. For this reason, it is preferable than the standard GARCH model (Brooks, 2008, p. 406).. Moreover, the EGARCH model explains an asymmetric response of financial time series to a shock. Another GARCH-type model to explain asymmetries in the time series is TGARCH (1,1) Threshold GARCH model. It is one of the widely used a non-linear asymmetric model which was introduced by Glosten, Jaganathan and Runkle (1993) so it is also called as GARCH-GJR model (Brooks, 2008, p. 406). γ stands for the asymmetrical effect. If γ>0 then the leverage effect exists. If $\gamma \neq 0$, effects of shocks on volatility are asymmetric (Cil Yavuz, et al., 2008, p. 72)

Chapter IV. Empirical Results

The objective of this chapter is to present empirical findings of this study. For this reason, first the linear OLS model is employed to test the day of the week effect and then this model is tested for autocorrelation and ARCH effects. Second, according to the test results, non-linear GARCH type models are estimated to show the day of the week effect in the BIST100.

4.1. Day of the week effect

4.1.1. OLS Model

The OLS regression results for the full period, 2005:01 - 2014:04, indicate that all t-statistics of the estimated parameters are lower than the critical value at the 5% significance level. There is no significant coefficient of days; therefore, there is no significant relationship between days of the week and stock returns. The only significant relation is between the return and previous day return, which is significant at 10% level.

Adjusted-R^2 is very low, -0.08 %. F statistics of OLS regression is also low and not significant with the p-value of 0.6298. Thus, we cannot reject the null hypothesis of all coefficients are equivalent. There is no significant difference among daily returns. Thursday returns are the highest for the BIST 100 Index. This is consistent with descriptive statistics results. Daily returns for the whole period are positive for all days.

Below OLS regression equation [9] expresses the values of the day of the week returns coefficients for the whole period from January 2005 to April 2014. The values in brackets are t-statistics of each coefficient. The only significant coefficient according to t-statistics is lag return with the value of 0.0348. The biggest coefficient is D_4 which represent the difference between the mean returns of Thursday and Friday, but it is not significant. OLS result support the alternative hypothesis of unequal returns across the days of the week.

$$R_t = 0.0541 - 0.01893{*}D1 + 0.0013{*}D2 - 0.0461{*}D3 + 0.01767{*}D4 + 0.0348{*}R_{t-1} + \varepsilon_t \quad [9]$$

t-stat (0.15) (-0.16) (0.01) (-0.39) (0.15) (1.68)

Table 6: Day of the week returns of the BIST 100 Index and OLS results for each year

	Monday ($c+\beta_1$)		Tuesday ($c+\beta_2$)		Wednesday ($c+\beta_3$)		Thursday ($c+\beta_4$)	Friday (c)		Previous Day		R^2- adj	F-stat	p-value
2005	-0.175	*	-0.145		-0.363		0.041	0.298	*	0.098	*	-0.2%	0.897	0.483
2006	-0.303		0.03		-0.014		0.442	-0.039		0.04		-0.2%	0.919	0.469
2007	-0.188		-0.371		-0.125		-0.102	0.305		-0.043		-1.4%	0.333	0.892
2008	-0.135		0.171		-0.374		-0.097	-0.169		0.12	**	-0.2%	0.892	0.486
2009	0.184		-0.255		0.457		0.316	0.122		0.023		-0.1%	0.938	0.456
2010	0.855	***	0.451	*	0.608	**	0.353	-0.37		0.03		1.7%	1.85	0.103
2011	-0.323		0.267		-0.283		-0.226	0.012		-0.001		-0.3%	0.857	0.51
2012	-0.107		0.001		-0.113		-0.109	0.237		-0.017		-1.7%	0.144	0.981
2013	-0.057		-0.201		-0.244		-0.374	0.113		-0.079		-0.8%	0.613	0.689
2014	0.087		-0.074		-0.195		-0.238	0.02		-0.095		-4.8%	0.243	0.941
2005-2009	-0.024		-0.018		0.026		0.208	0.088		0.068	***	0.3%	1.646	0.144
2010-2014	0.099		0.147		-0.001		-0.084	-0.001		-0.031		-0.1%	0.792	0.555
2005-2014	0.035		0.055		0.008		0.072	0.054		0.034	*	-0.1%	0.629	0.676

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6 illustrates OLS results for the day of the week effect on a yearly basis. Last three rows include the results for the whole period and the sub-periods of the data. F-statistics of each year and sub-periods have insignificant values.

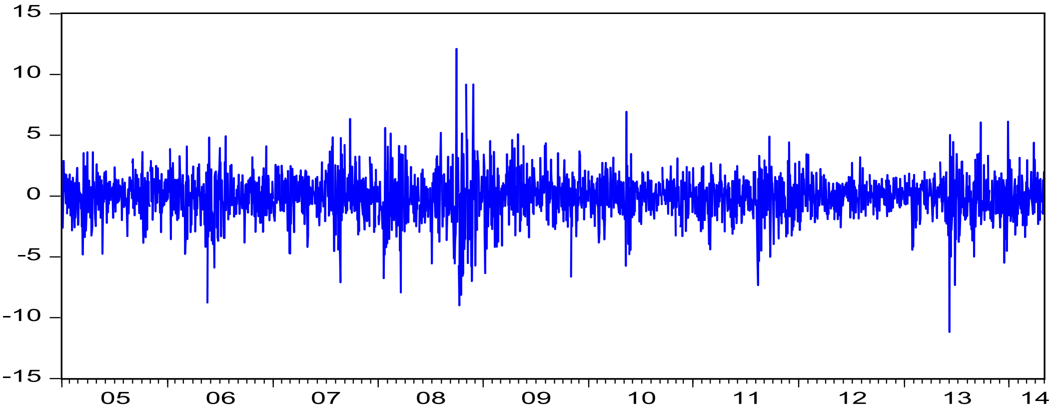
Negative Monday return can be examined for most of the years and for the first half of the data (2005-2009) but there is significant positive Monday return at 1% level in 2010. For 2010, the highest return on Monday is followed by positive and significant Wednesday and Tuesday returns respectively.

For the first half of the data, the previous return parameter is highly significant at 1% level. Friday returns are positive, but insignificant; Monday and Tuesday returns are negative but insignificant. For the second five-year sub-period (2010-2014), none of the coefficients is significant including previous day return. This indicates that the null hypothesis of equal mean returns for each day cannot be rejected for the sub-periods of the data as well. While Monday has the highest return, which is consistent with findings of Cicek (2013), Friday has the lowest and negative gain for the period of 2010-2014.

OLS is a linear model that may be not enough to explain all features of the data set. For example, leptokurtosis, volatility clustering, leverage effects cannot be well represented by linear structural models (Brooks, 2008, p. 380). The BIST 100 Index is leptokurtic with fat tails and high kurtosis value as described in summative statistics in Chapter three.

By examining below Figure 4, it can be concluded that the data has volatility clustering feature. Mandelbrot (1963, p. 418) explains volatility clustering in the movement of prices as *"large (small) changes are prone to be followed by large (small) changes- of either sign".* This time series of the BIST 100 Index returns shows that large changes are likely to cluster together.

Figure 4: Graph of residuals of the BIST 100 Index Return



Check for Autocorrelation and ARCH Effects

ACF in the residuals is plotted in Figure 5 to check autocorrelation with a qualitative examination. 36 lags are shown along the horizontal axis and autocorrelation values are shown on the vertical axis. Figure 5 indicates significant autocorrelation in most of the lags which are generally non-zero after lag6. Thus, the null hypothesis of no serial correlation in residuals can be rejected.

Figure 5: Correlogram of residuals the BIST 100 Index

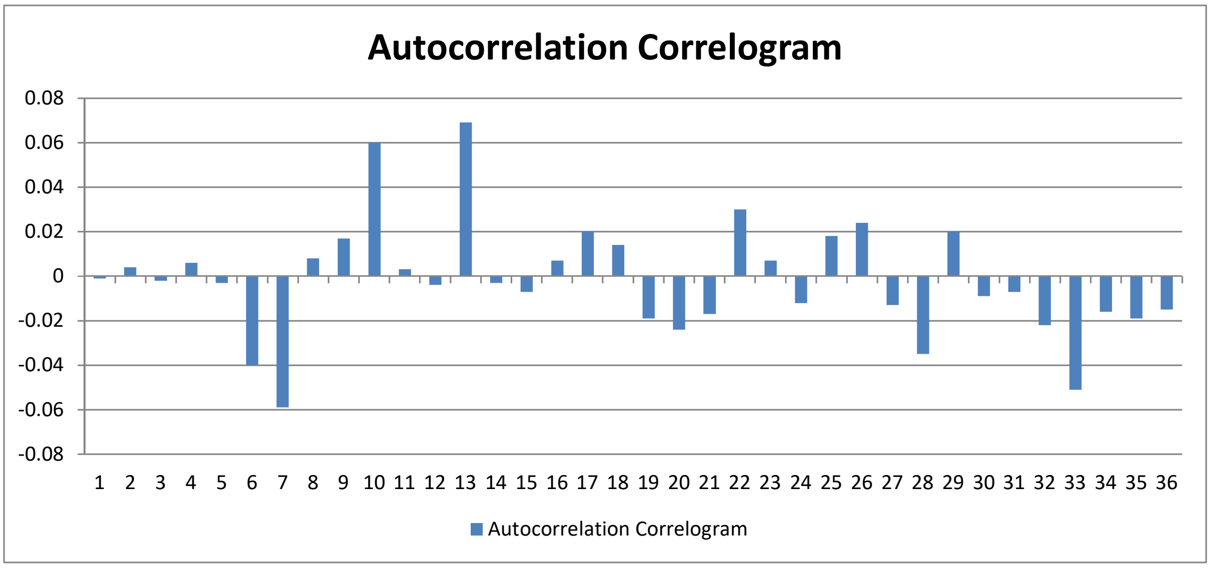
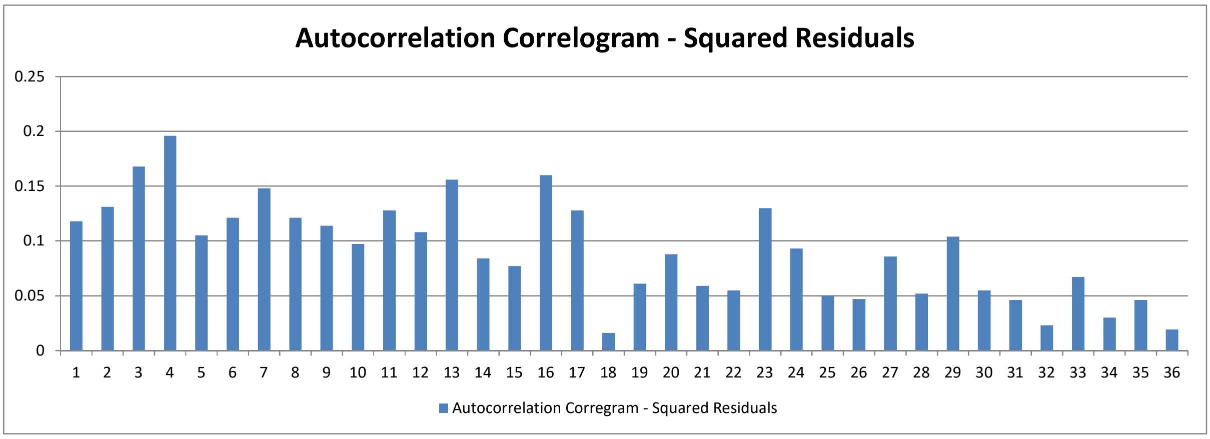


Figure 6 shows the correlogram of squared residuals. The null hypothesis of no autocorrelation in the squared residuals can also be rejected by examining significant deviations from zero in the Figure 6.

Figure 6: Correlogram of squared residuals the BIST 100 Index



Results for PACF correlogram were not presented here due to close similarity to ACF correlogram. Besides qualitative examinations by plotting ACF correlogram, quantitative examinations are also needed. For this reason, Ljung-Box Q-Test and Engle's (1982) ARCH test are applied to check autocorrelation and ARCH effects in residuals.

Ljung-Box Q-test on return statistics are calculated up to lag 36. Only the Q-statistics for lag 36 is presented. Q (36) = 55.115** (0.022) indicates that Q-statistics for lag 36 is significant at 5% level. Hence, the null hypothesis of no autocorrelation is rejected.

Ljung-Box Q-test on squared residuals Q^2 (36) = 871.05*** (0.00) shows that Q-statistics for lag 36 is significant at 1% level. There is strong evidence to reject the null hypothesis of no autocorrelation in squared residuals. This is significant evidence in support of ARCH effect.

ARCH effects are calculated for estimating whether GARCH-type models are appropriate for data or not. The BIST 100 Index return shows evidence of ARCH effects with significant ARCH-LM and F version statistics at 1% level on Table 7. There is a strong support of ARCH and GARCH effects in the return series. Therefore, GARCH models can be used for modelling conditional variance.

Table 7: Heteroskedasticity Test: ARCH-LM test

F-statistic	32.70905	Prob. F(1,2324)	0.0000
Obs*R-squared	32.28284	Prob. Chi-Square(1)	0.0000

4.1.2. GARCH (1,1), EGARCH (1,1), TGARCH (1,1) Model Results

Table 8 shows the findings from three GARCH (1,1) type models. Coefficient values and z-statistics for each mean equation and variance equation are presented. The first two columns report the results from the standard GARCH (1,1) estimation, the second one reports the EGARCH (1,1) model, the third column is for the results of the TGARCH (1,1) model. All parameters for the days in the mean equation are insignificant. According to the results, the only significant coefficient is the lagged return (R_{t-1}). Lag return is statistically significant at 5% level in EGARCH model, at 1% level in GARCH and in TGARCH models. All parameters of variance equations of GARCH models are significant at 1% level.

The results of GARCH models also indicate that there is no significant evidence to reject the null hypothesis of equality of daily mean returns. This means that the day of the week effect is not available for the return time series. These results are similar to OLS results. Hence, OLS results are robust by applying GARCH models.

Table 8: Parameter estimates for GARCH models with the Normal Distribution

	ESTIMATED MODELS					
	GARCH		EGARCH		TGARCH	
Mean Equation						
	Value	**Z-stat**	**Value**	**Z-stat**	**Value**	**Z-stat**
C	0.0826	1.1453	0.0306	0.4294	0.0318	0.4266
Monday	0.0653	0.6668	0.1091	1.1340	0.0984	0.9810
Tuesday	0.0057	0.0560	0.0420	0.4147	0.0162	0.1576
Wednesday	0.0733	0.7364	0.0624	0.6338	0.0915	0.9086
Thursday	0.1159	1.2136	0.0827	0.8800	0.0870	0.8958
R_{t-1}	0.0316	1.3692*	0.0461	2.0510**	0.0414	1.7755*
Variance Equation						
ω	0.1210	5.5303***	-0.1045	-6.4246***	0.1615	6.5552***
ARCH(α)	0.1177	11.1616***	0.2083	10.2011***	0.0466	3.8079***
GARCH(β)	0.8482	65.3255***	0.9429	128.0239***	0.8327	59.1925***
γ			-0.1010	-10.1276***	0.1379	8.7116***
$AdjR^2$		-0.004		-0.002		-0.002
AIC		3.867		3.849		3.850
SIC		3.889		3.874		3.875
LL		-4490.562		-4469.284		-4469.874
Diagnostic Checking						
ARCH-LM(1)		-0.0029 (0.88)		-0.0183 (0.38)		-0.0260 (0.21)
Q(36)		30.722 (0.72)		28.849 (0.79)		29.457 (0.77)
$Q^2(36)$		23.020 (0.95)		30.922 (0.70)		27.782 (0.83)

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Numbers in brackets are p-values.

Moreover, non-linear asymmetric EGARCH, and TGARCH models indicate significant evidence for asymmetry in stock returns with the coefficient γ, which is significant at 1% level. This result is confirming the presence of the leverage effect in the return time series. Conditional variance coefficients α, β are significant at 1% level. The sum of α and β for the basic GARCH (1,1) model is 0.966. This value is very close to 1, which is indicating that the shocks to volatility permanent over time and it can be forecasted.

GARCH models are investigated with Normal distribution density function. When it is tried to use different distribution functions, e.g. student-t distribution or generalized error distribution (GED), results are also quite similar to the results to normal density functions. Thus, there is no need to show comparison of different density functions. Only the outcomes obtained with the Normal distribution density function are presented in this paper.

AIC- Akaike information criterion, SIC-Schwarz information criterion, and the LL-log-likelihood values reveal that EGARCH (1,1) models better estimate the return series than standard GARCH (1,1) and TGARCH (1,1) models.

Diagnostic Checking

Table 8 reports ARCH-LM test for lag 1 and Ljung-Box test for residual and squared residuals up to Lag 36. The results of all diagnostic tests indicate that there is no ARCH effect and there is no significant serial correlation. Therefore, it can be concluded that GARCH (1,1), EGARCH (1,1), TGARCH (1,1) are correctly specified. All models are successful to estimate the conditional variance.

Sign Transitions from Friday to Monday

Percentages of positive gains are calculated yearly and results are shown at Table 9 on the second column. Overall, the BIST 100 Index has experienced positive gains in 53% of the period. Moreover, positive gains are greater than negative gains for each year, except the year 2008.

Table 9 also shows sign changes from Friday to Monday, those are the trading days divided by weekends. Most of the returns from Friday to Monday exhibit positive to positive (P to P) transitions 30% for the whole period. It means that positive Friday return may lead to positive expectations on Monday that cause positive returns on Monday. Table 9 shows yearly sign transitions as well. In 2013, the BIST 100 Index has faced the highest positive to positive transition by 42%. This positive relationship between signs of Friday return and following Monday return is consistent with the sign analysis of Balaban (1995, p.142) for the period 1988–1994, there was 32.5% positive to positive sign changes from Friday to Monday in the Turkish stock market. However, these results are contrary to Jaffe and Westerfield's (1989) argument of negative to positive (N to P) transition from Friday to Monday. According to Table 9, 24% of Friday to Monday transitions are negative to positive (N to P) transition. 23% positive to positive (P to P) and 23% negative to negative (N to N) transitions have occurred in the BIST 100 Index.

Table 9: Percentages of Positive Gains and % of Friday-to-Monday sign Changes

Years	%Positive Gains	P to P	P to N	N to P	N to N
2005	58%	38%	27%	21%	15%
2006	52%	24%	27%	20%	29%
2007	50%	23%	25%	23%	29%
2008	42%	24%	18%	24%	33%
2009	58%	27%	33%	29%	12%
2010	57%	33%	11%	39%	17%
2011	51%	24%	31%	18%	27%
2012	57%	39%	20%	20%	20%
2013	50%	42%	17%	17%	25%
2014	52%	24%	18%	35%	24%
Overall	53%	30%	23%	24%	23%

Start of the Week Effect

This effect has been analysed for additional evidence for the weekend effect. Although previous results show no significant existence of the day of the week effect in the Turkish stock market, it is found that the sign of Monday return has an effect on the gain of the rest of the week. Table 10 shows the mean daily returns for the weeks starting positive or negative Monday return. In this data set, if the return on Monday is positive, the average daily return for the week is also positive and 0.2806. If the first trading day is negative, the week has negative gain on average, -0.2188. These findings are consistent with the findings of Demirer & Karan (2002), which is to open a week with a positive return is a sign for positive gain from this entire week.

Table 10: Average daily returns for the week starting positive/negative Monday returns

	Monday(+)	Monday(-)
Average daily return for the week	0.2806	-0.2188

4.2. January Effect Results

For this data set, OLS results and descriptive statistics show no significant difference in the means of monthly returns. Thus, the null hypothesis of no January effect cannot be rejected.

Table 11 indicates average monthly returns estimation results from four different methodologies in each column. July has the highest return for the total dataset. January has negative mean return. However, there are insignificant results for average monthly returns according to all estimated models.

The last three rows show diagnostic tests. Engle's (1982) ARCH test and serial correlation Q-statistics results present significant results for OLS at 1% level, insignificant results for all GARCH type models. Thus, GARCH models are much better to represent the data for January effect. The most powerful model for future prediction could be the EGARCH (1,1) model that has the maximum Adjusted R^2 , 0.46%.

Table 11: January effect test results

	OLS	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
January	-0.02 (0.4485)	0.129 (0.1932)	0.07 (0.1656)	0.12 (0.5321)
February	0.009 (0.5064)	0.022 (0.847)	0.03 (0.5082)	-0.0 (0.7569)
March	0.083 (0.6244)	0.205 (0.3981)	0.23 (0.4287)	0.13 (0.606)
April	0.202 (0.927)	0.141 (0.7933)	0.14 (0.7086)	0.11 (0.7324)
May	-0.14 (0.5699)	0 (0.9102)	0.06 (0.8636)	-0.0 (0.8304)
June	-0.03 (0.1932)	0.096 (0.2838)	0.13 (0.4496)	0.01 (0.4774)
July	0.310 (0.4741)	0.3 (0.7009)	0.30 (0.8153)	0.25 (0.6874)
August	-0.07 (0.252)	0.049 (0.3891)	0.07 (0.4175)	-0.0 (0.2456)
September	0.206 (0.3441)	0.284 (0.5369)	0.29 (0.5563)	0.28 (0.6222)
October	-0.03 (0.5662)	0.229 (0.4512)	0.22 (0.43)	0.20 (0.1842)
November	-0.08 (0.4758)	-0.036 (0.6895)	-0.0 (0.7742)	-0.0 (0.4429)
December	0.099 (0.3242)	0.16 (0.2628)	0.17 (0.2056)	0.07 (0.3199)
Adj. R^2	0.0006	-0.0037	-0.0046	-0.0023
Fstat(prob)	1.1289 (0.33)	-	-	-
LL	-4682.964	-4488.923	-4493.307	-4467.329
ARCHLM-1	33.39 (0.00)***	0.020 (0.8864)	0.26 (0.6050)	0.91(0.3392)
Q(36)	58.29 (0.01) ***	31.922(0.663)	31.431 (0.686)	31.595(0.678)
Q^2(36)	909.85 (0.00) ***	23.186(0.951)	32.419 (0.640)	29.358(0.775)

***** indicates %1 significance level. LL is Log-Likelihood values.**
Numbers in brackets are p-values. TGARCH is also called as GARCH-GJR.

F-statistics (1.1289) for OLS is not significant. Log-Likelihood values are lower for GARCH-GJR and EGARCH models. These findings are in line with recent studies carried out by Atakan (2008), Cinko (2008), Tuncel (2012) in Turkey.

4.3. Turn of the Month Results

Empirical findings of this study show that the strong evidence for the turn of the month effect is found for the BIST 100 Index over the period of 2005-2014.

Table 12: Turn of the month daily percentage returns

Trading Day	2005-2014	2005-2009	2010-2014
-9	-0.12	-0.30	0.10
-8	0.09	-0.03	0.21
-7	-0.31*	0.10	-0.78***
-6	0.11	0.39	-0.21
-5	0.08	0.31	-0.18
-4	0.08	-0.01	0.18
-3	-0.03	0.16	-0.27
-2	0.44**	0.51**	0.36*
-1	**0.34****	**0.44***	**0.22**
1- first day	**0.20**	**0.14**	**0.26**
2	**0.36****	**0.41**	**0.31**
3	**-0.11**	**-0.26**	**0.07**
4	**-0.02**	**-0.10**	**0.07**
5	-0.21	-0.15	-0.29
6	-0.09	-0.11	-0.07
7	0.05	0.09	-0.01
8	0.05	0.06	0.04
9	0.08	-0.17	0.36*

***, **, * indicates significance at 1% level, 5% level, 10% level, respectively.

Table 12 shows daily percentages of stock returns around the turn of the month from -9 to +9 for eighteen days. The first and second half of the data is also separately estimated. “1” represents the first trading day of months. It can be observed from the table that mean returns are significant for the day before the first day (-1), as well as for the day (-2) and (2).

Table 13 displays the estimation outcomes for the five-day turn of the month effect. There are significant results to show mean return around turn of the month is different as well as higher from the mean return for the rest of the month. F statistics for OLS is significant at 10% level with the value of 2,65. This result is consistent with the literature that positive and larger return is observed in the first trading days of the month.

The last three rows of Table 13 are dedicated to diagnostic checking. The results show GARCH type models better represents the data than OLS model, which has an autocorrelation in residuals and ARCH effect. ARCH test, Ljung-Box test for residuals and Ljung-Box test for squared residuals are significant in OLS estimation, but they are insignificant in GARCH type models.

According to results, coefficients of GARCH (1,1) model are statistically significant at 1% level. While mean return of the turn of the month is 0.280, mean return for the rest of the month is 0.092. It means the average return has doubled within the turn of the month days. Adjusted R^2 for the GARCH (1,1) model is approximately 0.2% which is the highest among other estimation models. The coefficient γ, which signifies the asymmetric feature of volatility, is significant at 1% level.

Table 13: Turn of the month effect estimation results – 2005-2014

	OLS	**GARCH (1,1)**	**EGARCH (1,1)**	**TGARCH (1,1)**
Mean Equation				
ROM (c)	0.011	0.092***	0.064*	0.059*
TOM (c+ β_1)	0.154*	0.280***	0.217**	0.219**
Variance Equation				
ω		0.120***	-0.10***	0.163***
ARCH(α)		0.119***	0.210***	0.050***
GARCH(β)		0.847***	0.943***	0.830***
γ			-0.09***	0.132***
Adj-R^2	0.00071	-0.001956	-0.000232	-0.00014
F-statistics	2.65*			
LL	-4687.86	-4491.095	-4471.297	-4471.839
AIC	4.03	3.86	3.85	3.85
Diagnostic Checking				
ARCH-LM(1)	30.761***	0.0212	0.696	1.467
Q(36)	60.764***	37.281	35.405	36.472
Q^2(36)	883.73***	21.237	29.285	26.448

Chapter V. Concluding Remarks

This chapter aims to summarize the findings of the empirical study on calendar effects. Main conclusions will be reviewed. Moreover, limitations of the study and recommendations for further research will be provided.

5.1. Conclusion

In the literature, the existence of the seasonal anomalies on stock returns has been widely documented for the Turkish stock market. In this study, no significant relations have been found between days and stock returns as well as between months and stock returns. However, it is discovered that, days around the turn of the month have significantly positive and higher returns. By using four separate models, OLS, GARCH (1,1), EGARCH (1,1), GARCH-GJR (1,1), this paper has tested the day of the week effect, the January effect, and the turn of the month effect for the BIST 100 Index returns. Estimation results have indicated that there is no variance in the returns across the days of the week as well as no significant difference across months of the year. The only significant result has obtained for the turn of the month effect. The mean return of the turn of the month days was greater than the mean return over the entire month for the period of 2005-2014. The results were robust by applying GARCH type models, which are much better specifications than OLS. To sum up, days around the turn of the month are significantly different than other days. This anomaly could be exploited by forming a trading strategy according to this calendar pattern. Thus, efficient market hypothesis was not supported for the Turkish stock market due to the availability of some calendar anomalies in stock returns.

In addition to investigation of non-existence of the day of the week effect, the start of the week effect was also researched. It is found that the sign of Monday return influences the mean return of the remaining trading days of the week. Moreover, it was observed that the majority (30%) of sign changes from Friday to Monday show positive to positive (P to P) transitions in the BIST 100 Index returns.

5.2. Limitations and Suggestions for Further Studies

In this study, the BIST 100 Index was merely examined. However, calendar anomalies can be valid for other indexes[6] or for each individual share. Thus, dataset might not be fully representative for the Turkish stock market. Future studies can be focused on individual shares or other indexes.

Furthermore, different methodologies can be employed to test seasonality and market inefficiencies. OLS and GARCH models are distribution dependent so this study has limitations using only normal distribution.

Longer data set have created different results according to the study of Lakonishok & Smidt (1988). However, in this study, ten-year data has been used. The time can be extended to improve the results of calendar effects because the results may be influenced by the time period analysed. More calendar anomalies can be included in research to analyse market efficiency. Moreover, return calculation can be adjusted to the inflation.

[6] Borsa Istanbul has 342 stock indices, such as city indices, dividend indices.
http://borsaistanbul.com/en/indices

References

Abdioglu, Z. & Degirmenci, N., 2013. Seasonal Anomalies in Istanbul Stock Exchange. *Business and Economics Research Journal,* 4(3), pp. 55-73.

Abraham, A. & Ikenberry, D. L., 1994. The individual investor and the weekend effect. *Journal of Financial and Quantitative Analysis,* 29(2), pp. 263-277.

Agrawal, A. & Tandon, K., 1994. Anomalies or Illusions? Evidence from Stock Markets in Eighteen Countries. *Journal of International Money and Finance,* Volume 13, pp. 83-106.

Aksoy, M., 2013. Day of the Week Anomaly for Istanbul Gold Exchange: Gold and Silver Data. *The Journal of Accounting and Finance,* Volume January, pp. 149-152.

Aktas, H. & Kozoglu, M., 2007. The GARCH Model-Based Test of the Day of the Week Effect at Istanbul Stock Exchange. *Finans Politik & Ekonomik Yorumlar,* 44(514), pp. 32-45.

Akyol, A. C., 2006. *Calendar anomalies in The Istanbul Stock Exchange: Are they still there?,* The University of Alabama: Finance, and Legal Studies Working Paper.

Al-Jafari, M. K., 2012. An Empirical Investigation of the Day-of- the-Week Effect on Stock Returns and Volatility: Evidence from Muscat Securities Market. *International Journal of Economics and Finance,* 4(7), pp. 141-149.

Apolinario, R. M. C., Santana, O. M., Sales, L. J. & Caro, A. R., 2006. Day of the Week Effect on European Stock Markets. *International Research Journal of Finance and Economics,* Volume 2, pp. 53-70.

Ariel, R., 1987. A Monthly Effect in Stock Returns. *Journal of Financial Economics,* Volume 18, pp. 161-174.

Atakan, F. T., 2008. Testing the day-of-the-week effect and January effect anomalies at Istanbul. *Istanbul University Journal of the School of Business Administration,* 37(2), pp. 98-110.

Atakan, F. T., 2009. The Modelling of Volatility at the Istanbul Stock Exchange with ARCH-GARCH models. *Yonetim Dergisi,* Volume 62, pp. 48-61.

Balaban, E., 1995. Day of the week effects: new evidence from an emerging stock market. *Applied Economics Letters,* Volume 2, pp. 139-143.

Basdas, U., 2011. The day-of-the-week effect for Istanbul stock exchange: a stochastic dominance approach. *Journal of Applied Finance & Banking,* 1(4), pp. 223-238.

Basher, S. A. & Sadorsky, P., 2006. Day-of-the-week effects in emerging stock markets. *Applied Economics Letters,* 13(10), pp. 621-628.

Basher, S. A. & Sadorsky, P., 2006. Day-Of-The-Week Effects In Emerging Stock Markets. *Applied Economics Letters,* Volume 13, p. 621–628.

Berument, H. & Kiymaz, H., 2011. The Day of the Week Effect on Stock Market Volatility. *Journal of Economics and Finance,* 25(2), pp. 181-193.

Berument, M. H. & Dogan, N., 2012. Stock market return and volatility: day-of-the-week effect. *Journal of Economics and Finance,* Volume 36, pp. 282-302.

Bildik, R., 2004. *Are Calendar Anomalies Still Alive? Evidence from Istanbul Stock Exchange.* [Online]
Available at: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=598904
[Accessed 10 07 2014].

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics,* Volume 31, pp. 307-327.

Brooks, C., 2008. *Introductory Econometrics for Finance.* Second ed. Cambridge: Cambridge University Press.

Buyuksalvarci, A., 2009. Economic Crisis and Day of the Week Effect on the Istanbul Stock Exchange. *Selçuk Üniversitesi, İİBF,* pp. 108-126.

Chen, G., Kwok, C. & Rui, O., 2001. The day-of-the-week regularity in the stock markets of China. *Journal of Multinational Financial Management,* 11(3-4), pp. 139-163.

Cicek, M., 2013. The Day-of-the-Week Effect on Return and Volatility in the the Turkish stock markets. *Journal of Applied Finance & Banking,* 3(4), pp. 143-167.

Cil Yavuz, N., Guris, B. & Kiran, B., 2008. The Month and Holy Days Effects on the Volatility of Trade Deficit: Evidence from Turkey Nilgün. *Journal of Economic and Social Research,* 10(2), pp. 67-84.

Cinko, M., 2008. January effect in Istanbul Stock Exchange. *Journal of Dogus University ,* 9(1), pp. 47-54.

Coakley, J., Kuo, J.-M. & Wood, A., 2012. The School's Out effect: a new seasonal anomaly!. *British Accounting Review,* 44(3), pp. 133-143.

Compton, W., Kunkel, R. A. & Kuhlemeyer, G., 2013. Calendar anomalies in Russian stocks and bonds. *Managerial Finance,* 39(12), pp. 1138-1154.

Cross, F., 1973. The Behaviour of stock prices on Friday and Monday. *Financial Analysis Journal,* Volume November/December, pp. 67-69.

Demirer, R. & Karan, M. B., 2002. An Investigation of the Day-of-the-Week Effect on Stock Returns in Turkey. *Emerging Markets Finance & Trade,* 38(6), pp. 47-77.

Dickey, D. A. & Fuller, W. A., 1979. Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association,* Volume 74, pp. 427-431.

Dicle, M. & Hassan, M. K., 2007. Day of the week effect in Istanbul stock exchange. *Scientific Journal of Administrative Development,* Volume 5, pp. 53-83.

Duman Atan, S., Ozdemir, Z. A. & Atan, M., 2009. Weak Efficiency on the Stock Exchange Market: An Empirical Study on ISE. *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi,* 24(2), pp. 33-48.

Eken, M. H. & Uner, T. O., 2008. Hisse Senedi Piyasalarında Takvim Etkileri ve İstanbul Menkul Kıymetler Borsasına İlişkin Bir Uygulama. *Borsa Istanbul Review,* 12(45), pp. 61-119.

Engle, R. F., 1982. Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica,* Volume 50, p. 987–1007.

Fama, E. F., 1969. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance,* 25(2), pp. 383-417.

Fama, E. F., 1991. Efficient Capital Markets: II. *The Journal of Finance,* 46(5), pp. 1575-1617.

Forbes, W., 2009. *Behavioural Finance.* West Sussex: Wiley.

French, K. R., 1980. Stock Returns and Weekend Effect. *Journal of Financial Eonomics,* Volume 8, pp. 55-69.

Gibbons, M. R. & Hess, P., 1981. Day of the Week Effects and Asset Returns. *The Journal of Business,* 54(4), pp. 579-596.

Glosten, L. R., R., J. & Runkle, D., 1993. On the relation between the expected value and the volatility of the normal excess return on stocks. *Journal of Finance,* Volume 48, pp. 1779-1801.

Güler, S. & Çimen, A., 2014. DAY OF THE MONTH EFFECT IN EMERGING MARKETS. *Journal of Yasar University,* 9(33), pp. 5636-5648.

Gultekin, M. & Gultekin, B., 1983. Stock Market Seasonality: International Evidence. *Journal of Financial Economics,* Volume 12, pp. 469-481.

Hepsen, A., 2012. Calendar Anomalies and Turkish Real Estate Investment Trusts (REITs). *International Journal of Economics and Finance,* 4(3), pp. 230-236.

Inamlik, A., Berument, H. & Kıymaz, H., 2004. The day of the week effect on stock return and volatility:The case of Istanbul Stock Exchange (ISE). *Iktisat Isletme ve Finans,* Volume 19, pp. 91-102.

Jaffe, J. & Westerfield, R., 1985. The Week-End Effect in Common Stock Returns: The International Evidence. *The journal of finance,* 40(2), pp. 433-454.

Karan, M. B., 2001. İstanbul Menkul Kıymetler Borsası Anomalileri. *Ege Akademik Bakış Dergisi,* 1(2), pp. 83-94.

Kohers, G., Kohers, N., Pandey, V. & Kohers, T., 2004. The disappearing day-of-the-week effect in the world's largest equity markets. *Applied Economics Letters,* 11(3), pp. 167-171.

Kucuksille, E., 2012. The Test Of January Effect In ISE Indexes. *The Journal of Accounting and Finance,* Volume January, pp. 129-138.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P. & Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics,* 54(1), pp. 159-178.

Lakonishok, J. & Maberly, E., 1990. The Weekend Effect: Trading Patterns of Individual and Institutional Investors. *The Journal of Finance,* 45(1), pp. 231-243.

Lakonishok, J. & Smidt, S., 1988. Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies ,* 1(4), pp. 403-425.

Maberly, E. & Waggoner, D., 2000. *Closing the Question on the Continuation of the Turn of the Month Effects: Evidence from the S&P 500 Index Future Contracts,* s.l.: Federal Reserve Bank of Atlanta.

MacKinnon, J. G., 1996. Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics,* Volume 11, pp. 601-618.

Mandelbrot, B., 1963. The Variation of Certain Speculative Prices. *The Journal of Business,* 36(4), pp. 394-419.

Nelson, D., 1991. Conditional heteroskedasticity in asset returns: a new approach. *Econometrica,* Volume 59, pp. 249-370.

Ogden, J. P., 1990. Turn-of-Month Evaluations of Liquid Profits and Stock Returns: A Common Explanation for the Monthly and January Effects. *The Journal of Finance,* 45(4), pp. 1259-1272.

Oguzsoy, C. B. & Guven, S., 2003. Stock returns and the day-of-the-week effect in Istanbul Stock Exchange. *Applied Economics,* Volume 35, pp. 959-971.

Osborne, M. F. M., 1962. Periodic structure in the Brownian motion of stock prices.. *Operations Research,* 10(3), pp. 345-379.

Penman, S. H., 1987. The distribution of earnings news over time and seasonalities in aggregate stock returns. *Journal of Financial Economics,* 18(2), pp. 199-288.

Reinganum, M., 1983. "The Anomalous Stock Market Behavior of Small Firms in January: Empirical Test for Tax-Loss Selling Effects. *Journal of Financial Economics,* Volume 12, pp. 89-104.

Rozeff, M. S. & Kinney, W. R., 1976. Capital Market Seasonality; Case of Stock Returns. *Journal of Financial Economics,* Volume 3, pp. 379-402.

Rubinstein, M., 2001. Rational Markets: Yes or No? The Affirmative Case. *Financial Analysts Journal,* Volume 57, pp. 15-29.

Schwert, G. W., 2001. Anomalies and Market Efficiency. In: *Handbook of the Economics of Finance.* Amsterdam: North Holland: s.n., p. Chapter 17.

Shleifer, A., 2000. *Inefficient Markets: An Introduction to Behavioral Finance.* s.l.:Oxford Scholarship Online.

Sullivan, R., Timmermann, A. & White, H., 2001. Dangers of data mining: the case of calendar effects in stock returns. *Journal of Econometrics,* 105(1), pp. 249-286.

Taylor, S., 1986. *Modelling financial time series.* New York: Wiley.

Taylor, S. J., 2005. *Asset price dynamics, volatility, and prediction.* Oxfordshire: Princeton University Press.

Thusara, S. C. & Perera, P., 2014. Day of the Week Effect of Stock Returns: Empirical Evidence from Colombo Stock Exchange. *Kelaniya Journal of Management,* 1(2), pp. 16-27.

Tuncel, A. K., 2008. A New Approach to Day of the Week Effect: ISE Case. *Trakya Üniversitesi Sosyal Bilimler Dergisi,* 10(2), pp. 246-271.

Tuncel, A. K., 2012. Istanbul Menkul Kıymetler Borsasında Yılın Ayı Etkisi. *Yonetim Bilimleri Dergisi,* 10(19), pp. 1-30.

Ulussever, T., Guran Yumusak, I. & Kar, M., 2011. The day-of-the-week effect in the Saudi stock exchange: A non-linear GARCH Analysis.. *Journal of Economic and Social Studies,* 1(1), pp. 9-23.

Wang, J.-K., Ojiako, U. & Wang, L., 2013. Calendar effects of the Chinese stock markets. *Int. J. Business and Emerging Markets,* 5(1), p. 67–82.

Wong, K. A., Huia, T. H. & Chan, C. Y., 1992. Day-of-the-week effects: evidence from developing stock markets. *Applied Financial Economics,* 2(1), pp. 49-56.

Wong, P. L., Neoh, S. K. L. H. K. & Thong, S. T., 1990. Seasonality in the Malaysian stock market. Asia Pacific. *Journal of Management,* Volume 7, pp. 43-63.