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Volatility Effect of Seasonal Variation on Borsa Istanbul: The Ramadan Case[1]

Alper YILMAZ[2], Zeliha CAN ERGÜN[3]

ABSTRACT

This study aims to investigate the volatility effect of seasonality during Muslim's holy month of Ramadan in Borsa Istanbul (BIST) at the basis of four main return indices of technology, service, industry and financial sector for the period 2000-2017. In the literature, it is emphasized that those moving calendar anomalies such as Ramadan may affect the volatility of stock returns due to Islamic beliefs of investors such as fasting, increase in religious rituals or increase in negative perception on speculative trading. In this study, Ramadan effect on stock returns and volatility are analysed by using dummy variables in regression and GARCH model respectively. An examination of trading data shows that average rates of return are unaffected during the month of Ramadan, and although it seems there is an increase in volatility, except in service sector it is not statistically significant.

Key Words: Stock Returns, Calendar Anomaly, Ramadan Effect

Mevsimsel Değişkenliklerin Borsa İstanbul Üzerindeki Oynaklık Etkisi: Ramazan Ayı Örneği

ÖZET

Bu çalışmanın amacı Borsa İstanbul'da işlem gören teknoloji, mali, hizmetler ve sanayi olmak üzere dört temel sektör bazındaki getiriler üzerinde Ramazan ayının herhangi bir oynaklık etkisi yaratıp yaratmadığını 2000-2017 dönemleri arasında incelemektir. Literatürde hisse senetleri üzerinde hareketli takvim etkisine dair çeşitli çalışmalar mevcut olup Ramazan ayının etkisi bu çerçevede incelenebilir, çünkü bu ayda oruç tutma, artan dini aktiviteler veya borsa işlemlerinin bir çeşit kumar olduğuna dair artan negatif algı etkili olabilmektedir. Bu çerçevede, Ramazan ayına ait olası etkileri araç değişken kullanıldığı regresyon ve GARCH modelleri ile tahmin edilmiştir. Bulgulara göre söz konusu ayda hisse senedi piyasası getirilerinin değişikliğe uğramadığı ve bu ayda oynaklığın arttığı gözlemlense de hizmet sektörü haricinde bulgular istatistiksel olarak anlamlı değildir.

Anahtar Kelimeler: Hisse Senetleri Getirisi, Takvimsel Oynaklık, Ramazan Etkisi

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[2] Yrd. Doç. Dr., Adnan Menderes Üniversitesi Söke İşletme Fakültesi, Uluslararası Ticaret ve İşletmecilik Bölümü, alper.yilmaz@adu.edu.tr
[3] Arş. Gör., Adnan Menderes Üniversitesi Söke İşletme Fakültesi, Uluslararası Ticaret ve İşletmecilik Bölümü, zeliha.can@adu.edu.tr

1. Introduction

The main argument of the Efficient Market Hypothesis (EMH) is that stocks in the market reflect all the relevant and available information. Thus, based on this hypothesis price changes are unpredictable and random which is called as "random walk" (Bodie, Kane and Marcus, 2014). However, because of some anomalies returns can be predicted by the investors in the markets. One type of anomalies is calendar/seasonal anomalies, and these types of anomalies show that "historical returns and volatilities of financial assets may exhibit consistent but unreasoned behaviours particular to specific time periods in contrast to the random walk hypothesis" (Olgun, 2007). As emphasized by Latif, et al. (2011) calendar anomalies are related with particular period such as day of the week, weekend or January effect. For example, according to the day of the week effect, returns and volatilities of stocks vary across days of the week (Berument, et al., 2004). These calendar effects such as day of the week and January are the fixed calendar effects and they were studied broadly in the finance literature. However, as emphasized by Seyyed, et al. (2005) the effect of moving calendar effects such as Ramadan have not received much attention. In the literature it is argued that religion can affect the investors' mood and behaviour (Gavriilidis, et al., 2015).

As stated by Khazali (2014) Ramadan is one of the widely celebrated traditions by the 1.6 billion Muslims around the world. The probable effects of Ramadan on investment decisions are listed in the below:

- In Ramadan people spend more time for religious rituals, thus the general economic activity may slow down (Husain, 1998).
- Security trading may also decline, because some Muslims consider speculative trading a form of gambling. Beside this kind of trading, use of leverage (margin trading) and trading in interest-based securities are believed to be prohibited by Islam, so the trading activities of these securities may decline during Ramadan (Seyyed, et al., 2005).
- The main purpose of the Ramadan due to the Islamic religion is to increase humanity by fasting, so during the Ramadan investors may be more emotionally sensitive to impact of external influences. Based on the positive psychology, religion encourages optimistic beliefs (Khazali, 2014). It is known that investor sentiment plays a large role in the movement of stock prices, so in Ramadan it is expected that changes in the general mood of the population will affect stock markets in Muslim countries (Al-Hajieh, et al., 2011).
- However, all the emotions may not be positive, so Ramadan also brings emotional uncertainty. Therefore, decisions are affected by emotions (Al-Hajieh, et al., 2011).

Based on the above information, this study aims to investigate the volatility effect of seasonality during Muslim's holy month of Ramadan in Borsa Istanbul at the basis of four main return indices of technology, service, industry and financial sector for the period 2000-2017. In this study, Ramadan effect on stock returns and volatility are analysed by using dummy variables in regression and GARCH model respectively. An examination of trading data shows that average rates of return are unaffected during the month of Ramadan, and although it seems there is an increase in volatility, except in service sector it is not statistically significant.

The paper is organized as follows: Section 2 will provide the summary of the existing studies, Section 3 will provide empirical analysis including the information on data and methodology. Section 4 gives the empirical results in detail, and finally Section 5 concludes the paper.

2. Literature Review

Several studies were conducted about Ramadan effect in various Islamic countries. Husain (1998) examined the Ramadan effect in the Pakistani equity market. Daily stock prices and indices were used which were selected from the Karachi stock exchange for the period 1989 and 1993. The effect of Ramadan on mean return was analysed by using simple regression equation and the Ramadan effects on stock returns volatility was examined by using GARCH model. It is found that although stock returns decline in the month of Ramadan, the reduction in general is not significant, so Ramadan does not affect the average return in the market significantly. In contrast, it is found that there is significant evidence of a decline in the volatility of stock returns in Ramadan.

Moreover, Seyyed et al. (2005) examined the effect of Ramadan on weekly stock returns and volatility of the overall Saudi stock market. Similarly, they used regression and GARCH model as a method. Their data are composed of weekly index values for the overall stock market, sector indices for each of the six major sectors, and log returns of index closing prices. The period is between 1985 and 2000. As a result, they concluded that none of the Ramadan coefficients are statistically significant, so the Saudi stock market weekly returns are not significantly different during the month of Ramadan from the other months. However, it is found that the effect on conditional volatility is significant and pronounced, and there is a reduction in volatility. It is also found that there is a reduction in trading activity during the month of Ramadan for the overall market and all the sectors except electricity.

Ramezani, et al. (2011) used daily and monthly observation in order to examine the Ramadan effect on Iranian stock market for the period 2002-2012. They also used regression analysis and GARCH model to estimate the results. It is found that there is a positive relationship between stock exchange index and Ramadan.

Laslty, Khazali (2014) examined the Ramadan effect in the daily stock returns of 15 Muslim countries. Different from the other studies, non-parametric stochastic dominance (SD) approach was used for the analyses, because this model has analytical advantages over parametric mean-risk model prominent in the literature. Their results indicate that the Ramadan effect exists in most of Muslim countries.

In Turkey, Ramadan effect on stock market was only analysed by Oguzsoy and Guven (2004). They studied the existence of the effect of Holy Days (the feast of Ramadan and Sacrifice) on stock returns at the Borsa Istanbul for the periods 1988-1999, and their paper was the first comprehensive attempt to analyse the performance of BIST with respect to Holy Days. They used daily returns of BIST100 and BIST30 stocks, and performed simple regression with dummy variable. The results show that in BIST there is an effect of holy days.

3. Data and Methodology

The data used in this study consist of daily index values of Borsa Istanbul 100 index (BIST 100) which is the main equity index in Turkey, and of four selected major sector indices; namely Industry, Service, Fiscal and Technology. The return data covers the period from August 2000 through June 2017, and there are 4257 number of observations during the indicated period. All the data were obtained from BIST data store. The dummy variables were used for the month of Ramadan (D=1 for Ramadan period, and 0 otherwise). When it is compared to the Islamic calendar, the month of Ramadan starts 11 days earlier than the previous year in the Gregorian calendar. The return of each stock was calculated as the difference between the natural log of the closing prices of the stock i from the natural log of closing prices of the stock i on the previous day, which is shown as;

$$R_t = \ln (P_t - P_{t-1}) \quad (1)$$

In Equation (1) R_t shows the return of stock i, P_t shows the closing price of stock i on day t, and P_{t-1} shows the closing prices of stock i on day t-1.

Financial time series, such as stock prices, exchange rates, and inflation rates, often exhibit the phenomenon of volatility clustering. Volatility clustering emerges when the prices show wide change for an extended period and it follows by the periods in which there is relatively calm period (Gujarati, 2004; p.856). Due to nature of financial time series it is highly important to predict future value at risk (VaR) in today's highly volatile global market conditions to get maximum profit. Value at Risk (VaR) probably the most widely used risk measure in the financial institutions which is introduced by J.P. Morgan. Accordingly, there are three models that help to manage portfolios more efficiently; Historical Data simulation, Monte Carlo simulation and Variance-Covariance approach (Ejder, 2011; p.30).

Until recently, correlation and variance of error term assumed to be constant over time that is, the squared expected value of all error terms is the same at any given point of time. This assumption is called as homoscedasticity. However, several empirical studies suggested that the variances of the error terms are not the same over time, and it may be reasonably expected to be larger for some points of time or the ranges of the data change more than for others. These changes are called as heteroscedasticity. In the presence of heteroskedasticity, regression coefficients for ordinary least squares regression are still unbiased, but the standard errors and confidence intervals will be too narrow that may give a false sense of precision. Therefore, instead of correcting this problem, analysts use ARCH and GARCH models that treat heteroscedasticity as a variance to be modelled (Engle, 2002, p.3).

In 1982, Robert Engle firstly introduced the autoregressive conditional heteroscedasticity (ARCH) model to assess the time-varying volatility for parameterizing conditional heteroscedasticity in a wage-price equation for the United Kingdom data. The ARCH models assume the variance of the current error term or innovation to be a function of the actual sizes of the previous time periods' error terms: often the variance is related to the squares of the previous innovations (Terasvirta, 2006; pp.2-3). That is; the error term u at time t can be correlated with the error term at time (t – 1) in an AR(1) scheme or with various lagged error terms in a general AR(p) scheme in financial time series such as stock prices, inflation rates, and foreign exchange rates (Gujarati, 2004, p.488). Because these markets are considered as highly volatile and speculative; one can observe that large and small errors tend to occur in clusters. It looks something like “autocorrelation in the heteroscedasticity”. Engle formulated the notion that information from the recent past might influence the conditional disturbance variance. Therefore, the conditional variance, or the volatility, of a variable will be modelled as (Vogelvang, 2005; p.193);

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{2}$$

where, $\alpha_0 > 0$, $\alpha_j \geq 0$, $j = 1, 2, \ldots q-1$ and $\alpha_q > 0$. This is necessary and sufficient condition for positivity of the conditional variance. However, in time series such as interest rates, exchange rates and stock and stock index returns, forecasting volatility is different from forecasting the conditional mean of a process; because volatility cannot be observed, so the question is how volatility should be measured. In this regard, Bollerslev (1986) extended the ARCH model by making the conditional variance, h_t, a function of lagged values of h_t, in addition to the lagged values of squared residuals. Due to success of predicting conditional variances and having adjustability to flexible lags ARCH model replaced by Generalized ARCH (GARCH) model. In this model, the conditional variance is also a linear function of its own lags and leads, GARCH (p, q) is defined by;

$$h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3}$$

where, $\alpha_0 > 0$, $\alpha_j \geq 0$, $\beta_j > 0$, $\alpha_q > 0$, $j = 1, 2, \ldots q$, is sufficient condition for the conditional variance to be positive and the innovation sequence $\{\varepsilon_i\}_{i=-\infty}^{\infty}$ is independent and identically distributed with $E(\varepsilon_0) = 0$ and $E(\varepsilon_0^2) = 1$. Also $\alpha_0 + \beta_i < 0$ is a necessary condition for stationarity. In equation (3), the first part is the mean equation and the second part is the variance equation. The most useful GARCH model in applications has been the GARCH (1,1) model, that means one lag and one lead, p = q = 1 in Equation (3) (Fryzlewicz, 2007; p.4).

To examine the Ramadan effects on daily stock returns and volatility for the BIST 100 index and the four sectors, the following GARCH model was estimated. In the equation, the Ramadan effect is indicated as a dummy variable ($D_{Ramadan}$). The lagged values of the return variable and the lagged error values capture the auto regressive (AR) and moving averages (MA) effects respectively. The AR and MA terms of order k are included in the equation to eliminate auto correlated residuals. Ljung-Box test statistics is used to evaluate the order of ARMA components.

$$r_t = \mu_0 + \alpha_t D_{Ramadan} + \sum_{i=1}^{k} \phi_i r_{t-i} + \sum_{j=1}^{k} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

The time-varying volatility is modelled as a GARCH (p, q) process to estimate the parameters of the variance equation (5). The orders of p and q in conditional variance are a linear function of past squared error and lagged variance. Equations (4) and (5) are estimated jointly using the Full Information Maximum Likelihood procedure to determine the effect of Ramadan on return and volatility.

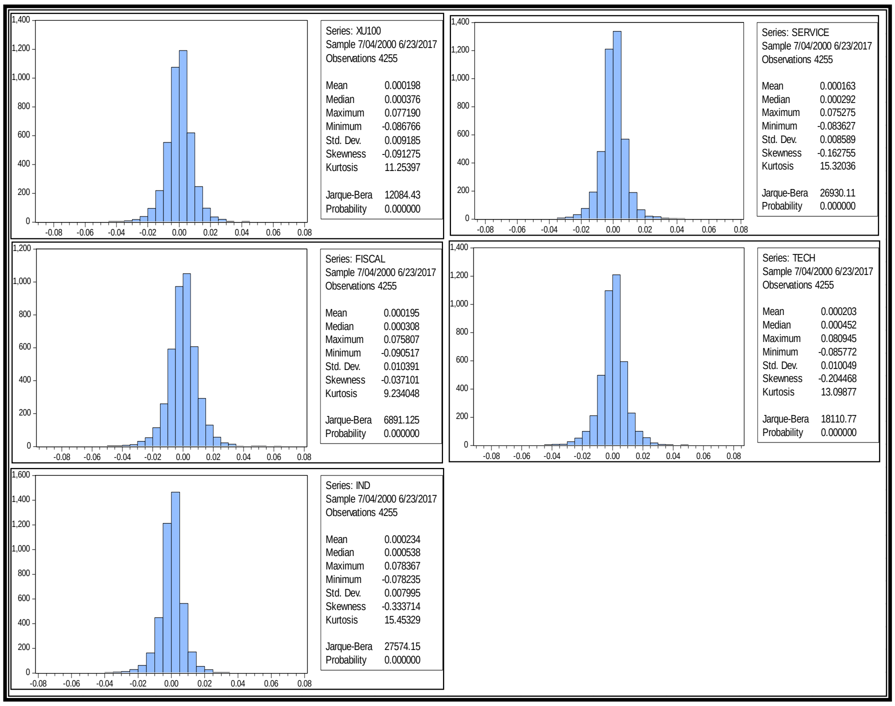
$$h_t = \nu_0 + \beta_t D_{Ramadan} + \sum_{i=1}^{p} \gamma_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j} \tag{5}$$

In Equation (5) ν_0, γ_i and δ_j are non-negative parameters to be estimated while p > 0 and q ≥ 0 defines the order of the ARCH process and β_t in the Equation (5) expresses the Ramadan effect on returns volatility. The non-negativity of the estimated parameters is required to obtain positive conditional variances. In addition, the restriction $\gamma_i + \delta_j < 1$ must be satisfied to ensure stationarity. Otherwise, if it equals 1 ($\gamma_i + \delta_j = 1$), the shocks to the current volatility are permanent (i.e., the volatility variable is non-stationary) and the time series exhibit presence of strong persistence.

4. Empirical Results

Before implementing the main model of the research question, the preliminary analyses were implemented for the determined dataset. Firstly, descriptive statistics (mean, variance, skewness and kurtosis levels) of the dataset were examined and the results are shown in Graph 1. Skewness is the third moment of normal probability distribution and it refers to measurement of symmetry, or more precisely, the lack of symmetry. Its value can be either positive or negative. A distribution with an asymmetric tail extending out to the right is referred to as positively skewed, while a distribution with an asymmetric tail extending out to the left is referred to as negatively skewed, and symmetric distribution means skewness equals to zero (Doane and Seward, 2011; pp.2-3). For our dataset, as shown in Figure 1, all variables are negatively skewed. On the other hand, kurtosis is a parameter that describes the shape of a random variable's probability distribution and can be formally defined as the standardized fourth population (β) moment about the mean. Distributions with positive kurtosis (leptokurtic), $\beta - 3 > 0$ has heavier tails and a higher peak, and distribution with negative kurtosis (platykurtic), $\beta < 0$ has lighter tails and is flatter in comparison with normal distribution (DeCarlo, 1997; 292). As observed from Graph 1, Kurtosis values of all variables are more than 3, and this indicates that distribution has heavier tails and a higher peak than the normal distribution. Therefore, from those kurtosis and skewness values it could be said that the dataset is not normally distributed, but to be more precise Jargue-Bera test statistic should be evaluated. According to Jarque-Bera test statistic, the null hypothesis of 'error terms are normally distributed' is rejected in terms of their probability values as shown in Graph 1; hence none of the series are normally distributed.

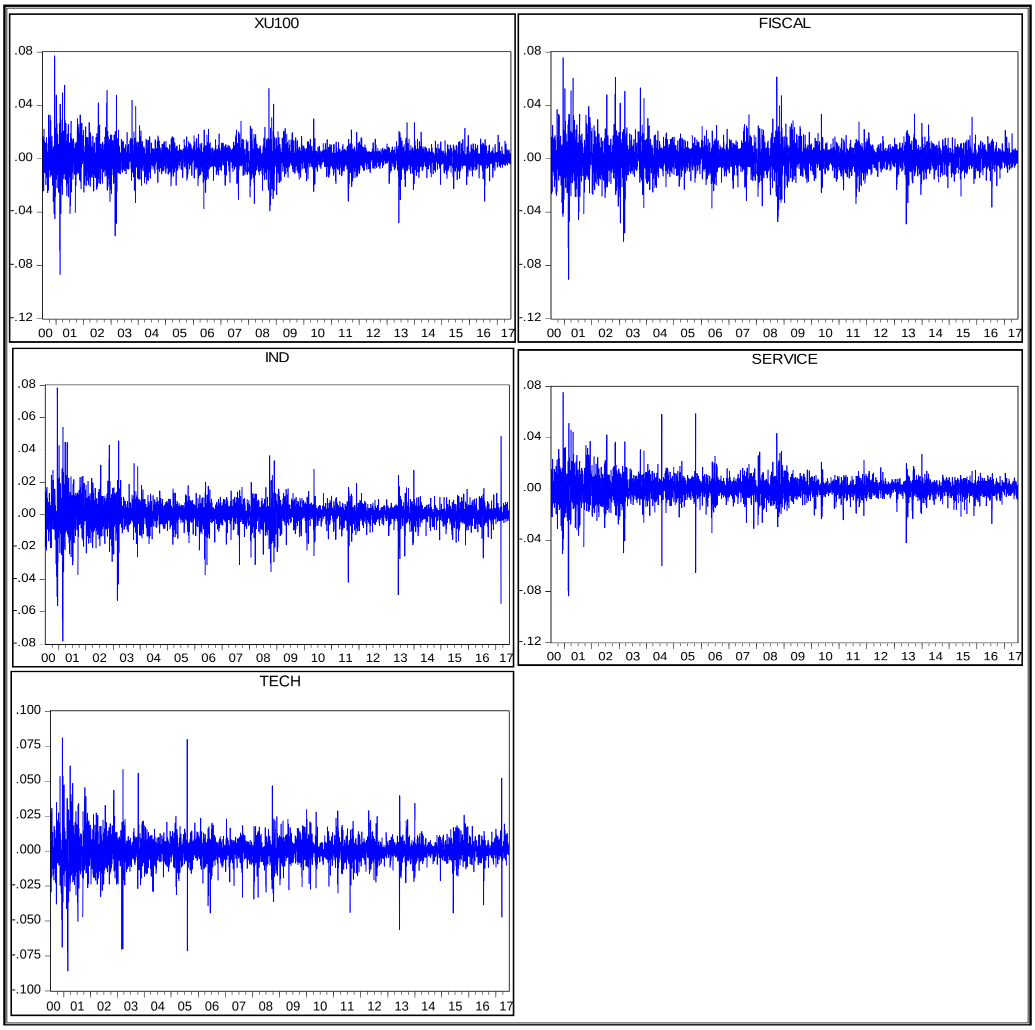
Graph 1. Descriptive Statistics and Distributions of Data Set



Secondly, in time series that follow a random process, it is extremely important whether the series are stable or not. Therefore, in order to check unit root visually it would be useful to see graphics of variables in level before the ARCH/GARCH analysis. Graph 2 below shows the time series plots of the three variables during the sample period. As it could be seen from the Graph 2; none of the series have not deterministic upward or downward trend. Therefore, it could be said that series are stable. Additionally, mean and standard deviation of the series have nearly zero values, and it gives clue about the stationarity of the variables.

Moreover, Graph 2 depicts volatility clustering in return series of five variables. In other words, from Graph 2 it is observed that there is prolonged period of high volatility from 2000 to 2003 and there exists prolonged period of low volatility from 2003 to 2009. That means period of high volatility are followed by periods of high volatility and period of low volatility tend to be followed by periods of low volatility. This suggests that residuals or error term is conditionally heteroscedastic. Each of these series appears to show the signs of ARCH effects in that the amplitude of the returns varies over time.

Graph 2. Time Series Plots of the Variables



Thirdly, if the arithmetic average and its variance of time series are stable, it means that variables do not show a systematic change. This type of time series is called as stable (Isik et al., 2004). So, it should be discussed the stationarity properties of the variables before ARCH/GARCH analysis, because if time series are not stable (non-stationary or show systematic change) the problem of 'Spurious Regression' may appear, and this will make a set of series seem as if it has a relation with another set of series (Basarir and Ercakar, 2016: 53). Thus, to build an appropriate model, all series must be stationary. Therefore, the unit-root structure of the data should be checked. In order to test for unit root, Augmented Dickey Fuller test, Modified Dickey-Fuller (DF-GLS) test, Phillips-Perron (PP) test and Point Optimal test were used as shown in Table 1. According to the results; the statistic values are smaller than the critical values and the p values are lower than %1 level. Therefore, the null hypothesis (unit root) has been rejected at conventional test sizes and it could be concluded that time series are stationary at level I (0).

Table 1. Unit Root Tests

Variables	*ADF t-Stat.*	Probability	Variables	*PP t-Stat.*	Probability
XU100	-64.985	0.00	XU100	-64.987	0.00
Fiscal	-64.826	0.00	Fiscal	-64.835	0.00
Ind	-65.303	0.00	Ind	-65.305	0.00
Service	-66.266	0.00	Service	-66.271	0.00
Tech	-64.397	0.00	Tech	-64.451	0.00
Variables	*Dickey-Fuller GLS t-Stat.*	Cric. Values (%1/%5/%10)	Variables	*ERS Point Optimal t-Stat.*	Cric. Values (%1/%5/%10)
XU100	-6.461	-2.56/-1.94/-1.61	XU100	0.014	1.99/3.26/4.48
Fiscal	-5.428	-2.56/-1.94/-1.61	Fiscal	0.015	1.99/3.26/4.48
Ind	-4.371	-2.56/-1.94/-1.61	Ind	0.019	1.99/3.26/4.48
Service	-4.184	-2.56/-1.94/-1.61	Service	0.021	1.99/3.26/4.48
Tech	-6.352	-2.56/-1.94/-1.61	Tech	0.011	1.99/3.26/4.48

After detecting stationarity of the variables, ARCH LM test will be conducted to determine whether ARCH effect exists or not. The first step of ARCH LM test is to decide an appropriate mean equation, and ARIMA/ARMA model was used for this purpose.

ARIMA model is derived by general modification of an autoregressive moving average (ARMA) model and generally used to analyse time series data for better understanding and forecasting. This model type is classified as ARIMA (p,d,q), where p denotes the autoregressive parts of the data set, d refers to integrated parts of the data set and q denotes moving average parts of the data set. There, p, d and q are nonnegative integers. The appropriate ARIMA model must be identified for the particular datasets and the parameters should have the smallest possible values such that it can analyse the data properly and forecast accordingly. The Akaike Information Criteria (AIC) is widely used measure for this purpose. It is used to quantify the goodness of fit of the model. When comparing two or more models, the one with the lowest AIC is generally considered to be closer with real data (Mondal et al., 2014; p.15).

For this purpose, alternative Autoregressive Integrated Moving Average (ARMA) models were checked by comparing its AIC. Moreover, Q-statistics and correlogram was implemented in order to determine that there is no significant pattern left in the autocorrelation functions (ACFs) and partial autocorrelation functions (PACFs) of the residuals which mean the residual of the selected model is white noise (Adebiyi, 2014; p.106). Table 2 shows the different parameters of autoregressive (p) and moving average (q) among the several ARMA model experimented upon. According to the analyses, ARMA (1; 4) for XU 100, ARMA (4; 2) for Fiscal, ARMA (4; 2) for Technology, ARMA (4; 1) for Service and ARMA (3; 1) for Industry index were determined to be the best, as shown in Table 2. The models were determined based on the smallest Akaike information criterion and relatively smallest standard error of regression.

Table 2. ARIMA estimation outputs For Return Index of Variables

Variable (XU100)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0002	0.0002	1.2086	0.2269
DUMMY	0.0001	0.0004	0.1969	0.8439
AR(1)	-0.0569	1.0154	-0.0561	0.9553
MA(1)	0.0608	1.0161	0.0598	0.9523
MA(2)	0.0180	0.0084	2.1461	0.0319
MA(3)	-0.0167	0.0225	-0.7427	0.4577
MA(4)	0.0091	0.0215	0.4246	0.6712
AIC	-6.5396			
S.E. Regression	0.0091			

Variable (TECH)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0002	0.0002	1.1987	0.2307
DUMMY	-0.0002	0.0005	-0.3638	0.7161
AR(1)	-0.1318	0.5689	-0.2317	0.8168
AR(2)	0.0317	0.0099	3.1825	0.0015
AR(3)	0.0239	0.0209	1.1423	0.2534
AR(4)	0.0214	0.0141	1.5212	0.1283
MA(1)	0.1430	0.5700	0.2509	0.8019
AIC	-6.3609			
S.E. Regression	0.0100			

Variable (FISCAL)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0002	0.0002	1.0119	0.3117
DUMMY	0.0002	0.0005	0.4345	0.6640
AR(1)	-0.3137	0.4616	-0.6796	0.4968
AR(2)	0.6362	0.4655	1.3667	0.1718
AR(3)	-0.0044	0.0114	-0.3866	0.6991
AR(4)	-0.0270	0.0111	-2.4301	0.0151
MA(1)	0.3195	0.4620	0.6915	0.4893
MA(2)	-0.6119	0.4676	-1.3087	0.1907
AIC	-6.2927			
S.E. Regression	0.0103			

Variable (SERVICE)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0001	0.0001	0.9675	0.3333
DUMMY	0.0003	0.0004	0.7521	0.4520
AR(1)	-0.2891	0.7088	-0.4079	0.6834
AR(2)	0.0000	0.0137	-0.0015	0.9988
AR(3)	-0.0200	0.0100	-1.9907	0.0466
AR(4)	0.0066	0.0194	0.3413	0.7329
MA(1)	0.2734	0.7089	0.3856	0.6998
AIC	-6.6737			
S.E. Regression	0.0079			

Variable (IND)	Coefficient	Std. Error	t-Statistic	Prob.
C	0.0003	0.0001	1.8736	0.0611
DUMMY	-0.0003	0.0004	-0.7841	0.4330
AR(1)	-0.1943	0.4388	-0.4427	0.6580
AR(2)	0.0071	0.0066	1.0688	0.2852
AR(3)	-0.0195	0.0099	-1.9718	0.0487
MA(1)	0.1931	0.4406	0.4383	0.6612
AIC	-6.8175			
S.E. Regression	0.0079			

However estimated ARMA model should also provide the stability condition. In Table 3, the results for the stability of selected ARMA models were shown. The inverse roots of ARMA polynomials were depicted. As it could be seen from the Table 3, all inverse roots of AR and MA process are less than 1, which means that selected ARMA models satisfy the stability conditions.

Table 3. Inverse Roots of ARMA Polynomial(s)

Variable: Xu100			**Variable: Ind.**		
AR Root(s)	Modulus	Cycle	AR Root(s)	Modulus	Cycle
-0.0569	0.0569		-0.3622	0.3622	
MA Root(s)	Modulus	Cycle	0.0839 ± 0.2160i	0.2318	5.2353
-0.2280 ± 0.2717i	0.3547	2.7690	MA Root(s)	Modulus	Cycle
0.1976 ± 0.1828i	0.2693	8.4180	-0.1931	0.1931	
Variable: Fiscal			**Variable: Service**		
AR Root(s)	Modulus	Cycle	AR Root(s)	Modulus	Cycle
0.6623	0.6623		-0.4554	0.4554	
-0.5263	0.5263		-0.0089 ± 0.2810i	0.2812	3.9208
0.0328 ± 0.0961i	0.1016	5.062329	0.184188	0.184188	
MA Root(s)	Modulus	Cycle	MA Root(s)	Modulus	Cycle
0.6865	0.6865		-0.2734	0.2734	
-0.4686	0.4686				
Variable: Tech.					
AR Root(s)	Modulus	Cycle			
0.4071	0.4071				
-0.3985	0.3985				
-0.0701 ± 0.3561i	0.3630	3.5592			
MA Root(s)	Modulus	Cycle			
-0.1430	0.1430				

After determining appropriate ARMA model the ARCH effect must be checked by using ARCH-LM test before modelling volatility by GARCH. As it could be seen from Graph 3, correlogram Q statistic probabilities of adjusted five ARMA models are lower than %1 which indicates that there is autocorrelation in all selected ARMA models.

Then, White test was conducted for error terms to detect Heteroscedasticity. The variance σ_u^2 is not constant, or in other words the disturbance term is not homoscedastic. It means that time series variances of the error terms are not equal, in which the error terms may reasonably be expected to be larger for some points or ranges more than others, are aiding to suffer from heteroscedasticity (Engle, 2014; p.2). As it could be seen from Table 4, null hypotheses "H0*: the variance of the disturbance term is constant"* was rejected at %1 level for all the selected ARMA models.

Graph 3. Correlogram Q Statistic for ARMA Models

Variable: XU100

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.000	-0.000	2.E-06	
		2	-0.000	-0.000	0.0009	
		3	0.001	0.001	0.0038	
		4	-0.001	-0.001	0.0085	
		5	-0.006	-0.006	0.1792	
		6	-0.055	-0.055	12.962	0.000
		7	-0.007	-0.007	13.189	0.001
		8	0.006	0.006	13.339	0.004
		9	0.030	0.030	17.224	0.002
		10	0.058	0.058	31.527	0.000
		11	-0.018	-0.019	32.936	0.000
		12	0.005	0.002	33.044	0.000
		13	0.022	0.022	35.205	0.000
		14	0.008	0.009	35.469	0.000
		15	0.019	0.024	37.067	0.000
		16	0.021	0.028	39.041	0.000
		17	-0.001	-0.002	39.045	0.000
		18	-0.011	-0.012	39.521	0.000
		19	0.021	0.020	41.423	0.000
		20	-0.017	-0.018	42.624	0.000
		21	-0.035	-0.031	47.959	0.000
		22	-0.037	-0.037	53.755	0.000
		23	-0.019	-0.023	55.296	0.000
		24	-0.003	-0.006	55.341	0.000

Variable: Ind.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.000	-0.000	4.E-07	
		2	0.001	0.001	0.0015	
		3	-0.001	-0.001	0.0059	
		4	0.000	0.000	0.0060	
		5	0.003	0.003	0.0485	
		6	-0.050	-0.050	10.551	0.001
		7	0.005	0.005	10.667	0.005
		8	0.021	0.021	12.486	0.006
		9	0.021	0.021	14.357	0.006
		10	0.065	0.065	32.556	0.000
		11	-0.019	-0.019	34.157	0.000
		12	0.005	0.002	34.263	0.000
		13	0.016	0.016	35.314	0.000
		14	0.007	0.008	35.500	0.000
		15	0.028	0.030	38.940	0.000
		16	0.029	0.035	42.513	0.000
		17	-0.005	-0.009	42.632	0.000
		18	-0.007	-0.010	42.857	0.000
		19	0.008	0.007	43.114	0.000
		20	0.002	-0.001	43.138	0.000
		21	-0.029	-0.025	46.825	0.000
		22	-0.047	-0.047	56.410	0.000
		23	-0.036	-0.042	62.103	0.000
		24	0.007	0.003	62.342	0.000

Variable: Fiscal

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.000	0.000	1.E-06	
		2	-0.001	-0.001	0.0016	
		3	-0.001	-0.001	0.0032	
		4	0.015	0.015	0.9973	
		5	-0.000	-0.000	0.9975	
		6	-0.041	-0.041	8.0972	
		7	-0.017	-0.017	9.3256	0.002
		8	0.007	0.007	9.5313	0.009
		9	0.030	0.030	13.446	0.004
		10	0.057	0.058	27.087	0.000
		11	-0.020	-0.020	28.862	0.000
		12	0.012	0.010	29.439	0.000
		13	0.020	0.018	31.212	0.000
		14	0.009	0.008	31.585	0.000
		15	0.019	0.023	33.175	0.000
		16	0.015	0.020	34.126	0.000
		17	0.004	0.004	34.209	0.000
		18	-0.006	-0.008	34.359	0.001
		19	0.034	0.032	39.325	0.000
		20	-0.019	-0.021	40.910	0.000
		21	-0.034	-0.031	45.990	0.000
		22	-0.028	-0.028	49.244	0.000
		23	-0.009	-0.012	49.575	0.000
		24	-0.011	-0.012	50.058	0.000

Variable: Service

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.000	0.000	9.E-06	
		2	-0.000	-0.000	0.0002	
		3	0.004	0.004	0.0662	
		4	0.010	0.010	0.5131	
		5	-0.017	-0.017	1.7203	
		6	-0.031	-0.031	5.9220	
		7	0.012	0.012	6.5015	0.011
		8	-0.002	-0.002	6.5189	0.038
		9	0.027	0.027	9.5648	0.023
		10	0.042	0.043	17.187	0.002
		11	-0.030	-0.031	20.991	0.001
		12	0.000	-0.001	20.992	0.002
		13	0.023	0.023	23.198	0.002
		14	0.006	0.006	23.360	0.003
		15	0.016	0.020	24.392	0.004
		16	0.011	0.012	24.906	0.006
		17	-0.014	-0.017	25.729	0.007
		18	-0.015	-0.014	26.690	0.009
		19	-0.009	-0.010	27.000	0.012
		20	0.002	0.002	27.012	0.019
		21	-0.025	-0.021	29.747	0.013
		22	-0.029	-0.032	33.432	0.006
		23	-0.035	-0.039	38.715	0.002
		24	0.003	0.002	38.754	0.003

Variable: Tech.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.000	0.000	9.E-05	
		2	0.001	0.001	0.0061	
		3	0.001	0.001	0.0146	
		4	0.000	0.000	0.0147	
		5	-0.014	-0.014	0.8653	
		6	-0.052	-0.052	12.267	0.000
		7	0.001	0.001	12.272	0.002
		8	0.027	0.027	15.305	0.002
		9	0.017	0.017	16.556	0.002
		10	0.077	0.077	41.820	0.000
		11	-0.013	-0.015	42.551	0.000
		12	-0.002	-0.005	42.564	0.000
		13	-0.004	-0.003	42.628	0.000
		14	0.005	0.008	42.722	0.000
		15	0.026	0.030	45.629	0.000
		16	0.033	0.040	50.299	0.000
		17	-0.004	-0.007	50.377	0.000
		18	0.008	0.003	50.675	0.000
		19	-0.017	-0.020	51.957	0.000
		20	0.001	-0.003	51.960	0.000
		21	-0.010	-0.003	52.352	0.000
		22	-0.014	-0.010	53.143	0.000
		23	-0.004	-0.006	53.223	0.000
		24	-0.002	-0.006	53.234	0.000

Table 4. White Heteroskedasticity Test for ARMA Models

Variable : XU 100			
F-statistic	6.24E+22	Prob. F(44,4210)	0.00
Obs*R-squared	4255	Prob. Chi-Square(44)	0.00
Scaled explained SS	21492.4	Prob. Chi-Square(44)	0.00
Variable : Fiscal			
F-statistic	3.88E+24	Prob. F(54,4200)	0.00
Obs*R-squared	4255	Prob. Chi-Square(54)	0.00
Scaled explained SS	17222.6	Prob. Chi-Square(54)	0.00
Variable : Ind.			
F-statistic	1.73E+24	Prob. F(43,4211)	0.00
Obs*R-squared	4255	Prob. Chi-Square(43)	0.00
Scaled explained SS	30372.1	Prob. Chi-Square(43)	0.00
Variable : Service			
F-statistic	6.58E+23	Prob. F(52,4202)	0.00
Obs*R-squared	4255	Prob. Chi-Square(52)	0.00
Scaled explained SS	29681.9	Prob. Chi-Square(52)	0.00
Variable : Tech.			
F-statistic	6.72E+25	Prob. F(43,4211)	0.00
Obs*R-squared	4255	Prob. Chi-Square(43)	0.00
Scaled explained SS	25777.7	Prob. Chi-Square(43)	0.00

From these results, it could be stated that both the presence of auto correlation and heteroscedasticity are signs of ARCH effect. However, Lagrange Multiplier (LM) tests must be carried out in order to be sure about ARCH effect. For this purpose, firstly dependent variables were regressed on independent variables (Ramadan dummy) and residuals were found with the following OLS regression:

$$\hat{e}_t^2 = \hat{\alpha}_0 + \hat{\alpha}_1 e_{t-1}^2 + ...\hat{\alpha}_p e_{t-p}^2 \qquad (6)$$

Then, the null hypothesis (H_0: $\hat{\alpha}_1 = \hat{\alpha}_2 = ...\hat{\alpha}_p = 0$; means that there is no ARCH effect) was tested. The test statistic (Obs*R-squared / $n{*}R^2$) is asymptotically distributed as chi-square distribution with q degrees of freedom (Wang et al., 2005; p.59). Table 5 shows Engle's LM test results. Both the F-test for the parameters of the lagged residuals and the $n{*}R^2$ –statistics were resulted. The null hypothesis of no ARCH is clearly rejected at the 1% significance level firmly indicate the existence of an ARCH effect (Volatility) in all the residual series.

Table 5. Engle's LM Test Results for Residuals from Selected ARMA Models

Variable: XU100			
F-statistic	440.2898	Prob. F(1,4252)	0.00
Obs*R-squared	399.164	Prob. Chi-Square(1)	0.00
Variable: Fiscal			
F-statistic	239.9882	Prob. F(1,4252)	0.00
Obs*R-squared	227.2735	Prob. Chi-Square(1)	0.00
Variable: Ind.			
F-statistic	1050.217	Prob. F(1,4252)	0.00
Obs*R-squared	842.5952	Prob. Chi-Square(1)	0.00
Variable: Service			
F-statistic	606.8038	Prob. F(1,4252)	0.00
Obs*R-squared	531.2714	Prob. Chi-Square(1)	0.00
Variable: Tech.			
F-statistic	634.5794	Prob. F(1,4252)	0.00
Obs*R-squared	552.4316	Prob. Chi-Square(1)	0.00

As a last step, towards analysis GARCH (1;1) model was built which was originally introduced by Bollerslev to provide a volatility measure for our data set. The simplest GARCH model is the GARCH (1, 1) model, which can be written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \qquad (7)$$

In Equation (7), the conditional variance of u at time t depends not only on the squared error term in the previous time period [as in ARCH(1)] but also on its conditional variance in the previous time period. The (1,1) in parentheses is a standard notation in which the first number refers to how many autoregressive lags or ARCH terms appear in the equation, while the second number refers to how many moving average lags are specified which here is often called the number of GARCH terms (Gujarati, 2004; p.862). Table 6 reports the estimation results of the GARCH (1, 1) model for the return (4) and volatility (5) equations separately for the overall BIST 100 stock market index and the four sectors. The first two columns report the return equation results with the Ramadan dummy variable. None of the dummy coefficients are statistically significant, implying that the BIST daily returns are not significantly different during the month of Ramadan from the other months according to return equation.

The last four columns of Table 6 report the estimation results of the conditional variance (h_t) equation. The effect on conditional volatility is positive, but they are not statistically significant. The results show an increase in volatility of daily returns during the month of Ramadan for the overall market and the constituent sectors, but except service index their coefficients are not statistically significant. The increase in volatility for the service index is statistically significant at the 5% and %10 levels. Moreover, both ARCH ($\gamma_i \varepsilon_{t-i}^2$) and GARCH term ($\delta_j h_{t-j}$) are statistically significant and positive but the coefficients of Ramadan dummies are little noticeable.

Table 6. Estimated Returns and Conditional Variance GARCH (1, 1) Model With Ramadan Dummy Variable

Description	Return (r_t)		Conditional Variance (h_t)			
	Constant (c)	Ramadan Dummy	Constant (c)	Ramadan Dummy	$\gamma_i \varepsilon_{t-i}^2$	$\delta_j h_{t-j}$
XU100	0.0001 (0.19)	0.0002 (0.85)	0.0005*** (0.00)	0.0002 (0.61)	0.0901*** (0.00)	0.9048*** (0.00)
Fiscal	0.0001 (0.28)	0.0002 (0.70)	0.0003*** (0.00)	0.0003 (0.44)	0.0716*** (0.00)	0.9174*** (0.00)
Industry	0.0002** (0.04)	-0.0002 (0.52)	0.0004*** (0.00)	0.0001 (0.63)	0.1567*** (0.00)	0.8052*** (0.00)
Service	0.0001 (0.30)	0.0002 (0.57)	0.0004*** (0.00)	0.0004** (0.04)	0.1779*** (0.00)	0.8081*** (0.00)
Technology	0.0002 (0.17)	-0.0001 (0.76)	0.0005*** (0.00)	0.0001 (0.99)	0.1638*** (0.00)	0.7966*** (0.00)

Finally, in Table 7, ARCH LM test results of estimated GARCH (1;1) models are represented. According to the F-statistic, under the null hypothesis of there is no ARCH effect is clearly accepted at the 1% significance level firmly indicate that GARCH (1;1) model removed existence of an ARCH effect (Volatility) in both the residual series.

Table 7: ARCH LM Test of GARC(1;1) Model

Variable : XU 100			
F-statistic	0.7932	Prob. F(1,4252)	0.37
Obs*R-squared	0.7934	Prob. Chi-Square(1)	0.37
Variable : Fiscal			
F-statistic	0.8831	Prob. F(1,4252)	0.35
Obs*R-squared	0.8834	Prob. Chi-Square(1)	0.35
Variable : Service			
F-statistic	4.3594	Prob. F(1,4252)	0.37
Obs*R-squared	4.3570	Prob. Chi-Square(1)	0.37
Variable : Technology			
F-statistic	2.4114	Prob. F(1,4252)	0.12
Obs*R-squared	2.4112	Prob. Chi-Square(1)	0.12
Variable : Industry			
F-statistic	1.1751	Prob. F(1,4252)	0.28
Obs*R-squared	1.1754	Prob. Chi-Square(1)	0.28

5. Conclusion

There are many studies that have been documented various calendar/seasonal anomalies in stock market returns. One of these seasonal anomalies is the Muslim's holy month of Ramadan. During the month of Ramadan it is believed that the stock market returns and volatility may change. Based on this information, in this paper, specifically, return data during the Muslim month of Ramadan for the Turkish Equity Market was analysed for the period 2000-2017. Using a GARCH specification it is shown that average rates of return are unaffected during the month of Ramadan and although it seems there is an increase in volatility, it is not statistically significant except in service sector. Only for service sector, it seems there is a significant increase in volatility during the month of Ramadan. These results are not consistent with the previous researches that were conducted in other Muslim countries.

Increase in return volatility during the month of Ramadan may be due to increased trading activity or investor behaviour stemming from a variety of factors. Some of the factors contributing to the behaviour during the month of Ramadan are: unchanged banking hours, disregarding Islam's prohibition against speculation and use of interest which would affect margin trading, lack of religious orientation of the market participants leading to higher interest in trading, among others.

These results could be the reason of majority of foreign investors that trade in BIST. Some previous researches in the behavioural finance literature show that investors generally follow the foreign investors. In other words, they show herd behaviour. Therefore, these results may be the indicator of the dominance of foreign investors in Borsa Istanbul.

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