MACROECONOMIC ANNOUNCEMENTS AND INTRADAY STOCK MARKET VOLATILITY

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MACROECONOMIC ANNOUNCEMENTS AND INTRADAY STOCK MARKET VOLATILITY

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ABSTRACT

MACROECONOMIC ANNOUNCEMENTS AND INTRADAY STOCK MARKET VOLATILITY

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This study examines the effects of interest and inflation rate announcements on stock market volatility by using a standard event study methodology. The BIST-30 Index volatility is modelled and forecasted by the multiplicative component GARCH model. This is one of the first studies where the announcement effects are analyzed on the basis of volatility forecasts produced by the multiplicative component GARCH. The announcement effects are observed clearly with the advantage of using high-frequency data. While the market reacts to inflation rate announcements during the first 5 minutes following the announcement, the market reaction to interest rate announcements is observed 15 minutes later and lasts longer. In addition, empirical findings suggest that the market's reaction to unfavorable interest rate surprises is longer than the reaction to favorable surprises. The thesis ends with a conclusion and an outlook to future studies and applications.

Keywords: Announcement Effect, Intraday Stock Market Volatility, Event Study, Multiplicative Component GARCH

ÖZ

MAKROEKONOMİK GÖSTERGE AÇIKLAMALARI VE GÜN İÇİ HİSSE SENEDİ PİYASASI OYNAKLIĞI

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Bu çalışmada, olay etkisi metodu kullanılarak, faiz oranı ve enflasyon açıklamalarının hisse senedi borsasındaki oynaklığı üzerindeki etkileri incelenmiştir. Daha önce olay etkisi analizi amacıyla kullanılmayan "multiplicative component GARCH" modeli BIST-30 Endeksinin oynaklığını modellemede ve tahmin etmede kullanılmıştır. Yüksek frekanslı veri kullanarak faiz ve enflasyon açıklamalarının borsadaki etkilerini açıkça gözlemlemek mümkün olmaktadır. BIST-30 Endeksi, enflasyon duyurularına yalnızca ilk beş dakika içinde tepki verirken, faiz oranı duyurularına tepkisi daha geç ve daha uzun süreli olmuştur. Ayrıca, sonuçlar piyasanın olumsuz faiz kararlarına olumlu kararlardan daha uzun süre tepki verdiğini göstermektedir.

Anahtar Kelimeler: Duyuru Etkisi, Gün İçi Borsa Getiri Oynaklığı, Olay Etkisi Çalışması, Multiplicative Component GARCH

To My Family

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LIST OF ABBREVIATIONS

ACF	Auto Correlation Function
BIST	Borsa Istanbul
CBT	Central Bank of Turkey
CPI	Consumer Price Index
ECB	European Central Bank
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
MAE	Mean Absolute Error
FED	Federal Reserve System
mcsGARCH	Multiplicative Component Standard Generalized Autoregressive Conditional Heteroscedasticity
MPC	Monetary Policy Committee
PACF	Partial Correlation Function
RMSE	Root Mean Squared Error
sGARCH	Standard Generalized Autoregressive Conditional Heteroscedasticity
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
TURKSTAT	Turkish Statistical Institute
U.K.	United Kingdom
U.S.	United States
UHF	Ultra High Frequency

CHAPTER 1

INTRODUCTION

With the increase in the availability of high-frequency data and facility to access such tick-by-tick financial data, modelling and forecasting financial intraday volatility becomes crucial for financial literature. Since high-frequency data has some stylized characteristics, different techniques and models have being developed to capture these particular facts. The volatility forecasts, which obtained mostly from GARCH type models, are being used to investigate the effects of different events, indicators or announcements. There is a huge literature of macroeconomic announcements effects on the financial markets mostly with daily data. On the other hand, in the studies, in which intraday data are used to measure the announcement effects, volatility was not modelled and forecasted by multiplicative component GARCH model.

After Central Bank of Turkey (CBT) switches to explicit inflation targeting regime in 2006, two main communication tools came into use for financial stability: interest rate and inflation rate announcements. These announcements are made every month at pre-determined dates and times. Therefore, the periodic announcement data are appropriate to be used for stock market volatility analyses. However, the micro-level effects of this type of economic announcements are not known for the Turkish stock market volatility.

After the researches for the announcement effect analyses, it can be seen that there is no such a study in Turkey or in another country, which uses the multiplicative component GARCH model to investigate the effect of announcements on stock market volatility. Also, there is no such a study in Turkey, which uses intraday data to analyze the impact of economic announcements. In this thesis, the effects of macroeconomic announcements, which are inflation rate and interest rate announcements, on the volatility of BIST-30 Index by using multiplicative component GARCH model with 5-minute data, which is detailed in the Methodology section. Therefore, the contributions of this thesis to the literature are to use mcsGARCH model to analyze the impacts of economic announcements on volatility, and specifically to investigate the periodic interest and inflation rate announcements within the scope of Inflation Targeting Regime in Turkey.

As a result of the model estimations, mcsGARCH model performs better than standard GARCH models for the high-frequency data in BIST-30 Index return. Additionally, findings of the event study indicate that while the inflation rate announcements increase the volatility just for the first 5 minutes, the response of BIST-30 to the interest rate announcements is slower and lasts longer.

CHAPTER 2

LITERATURE REVIEW

2.1. Overview of Announcements Effect Studies

The impact of macroeconomic news and monetary policy announcements to the financial asset prices are widely researched by many economists. Both scheduled and unscheduled announcements affect the return and volatility in financial markets [26] such as option markets [1, 35] and foreign exchange markets [2, 79]. For the foreign exchange market, Almeida, Goodhart, and Payne [4] contribute to the literature with the finding that scheduled announcements have a stronger and faster impact on foreign exchange market than unscheduled announcements. On the other hand, Mensi et al. [79] could not find any significant effect of scheduled announcements on the conditional foreign exchange market volatility while unscheduled ones have significant effects. For the stock market volatility, Bomfim [24] found that the magnitude of the announcement effect on market volatility does not depend on whether the announcement is scheduled or not. Bredin et al. [25] studied the impact of U.S. monetary policy announcements on the Irish stock market volatility and witness that the announcements from both scheduled and unscheduled meetings have a positive and significant increase in the stock market volatility. Bernanke and Kuttner [17] omitted the announcements from unscheduled FOMC meetings since they are accepted as outliers making ordinary least-squares (OLS) estimation more sensitive.

In the literature, some economists studied the effect of scheduled announcements on the foreign exchange markets [4, 34, 57, 60], some others examine this effect for the bond market [13, 21, 63]. Relevant to this study, scheduled announcement effect for stock market is investigated by many economists such as [49, 53, 65, 78, 85, 86, 88].

Similar to the shocks in announcements schedule, the shocks in the amount of change can also alter the level of announcement effect. Among those investigating announcement effect by separating expected and unexpected changes, economists measure different type of announcements on different dependent variables. As the pioneers of those researchers, Cornell [30] examines the effects of unanticipated part of money supply announcements on real interest rate and the exchange rate; Frankel and Hardouvelis [48] examine the effect of unexpected changes in money announcements on commodity prices; Engel and Frankel [36] found an explanation of the effects of unanticipated changes in money supply announcements on real interest rate and exchange rate; and Hakkio and Pearce [56] analyzes the impact of in monetary policy, inflation and unemployment rate announcements on spot exchange rates by dividing expected and unexpected components. Urich and Wachtel [100] and Smirlock [93] examine the effect of inflation announcements on interest rates by the similar approach.

For the effects on stock market returns, many economists separate the economic announcement into expected and unexpected components by using market survey data served by money market authorities for the expected part. The results are similar for the researches using this separation for the U.S. economic announcements and NYSE: the stock market reacts significantly to the unexpected part of the changes but not to expected ones due to the efficient markets hypothesis [19, 30, 61, 74, 75, 85, 86, 88, 91, 94]. In addition to the market surveys, futures rate can also be used to infer the expected part of the announcements [19, 24, 54, 55, 71, 90], and the results are compatible with the studies using survey. Other than the market survey and futures rate, Lobo [75] used the short-end of the Treasury securities in order to identify the investors' expectations for the first time and found that estimations for the stock market prices using market survey data are more precise. Similarly, Bomfim [24] and Kurov [70] examine the announcement effect on stock market by using Treasury securities, which is the same variable for expected component used in this study. In addition to the studies for US, there are some studies for European markets. Bohl et al. [19] investigate the European stock market reaction to unexpected interest rate decisions by European Central Bank (ECB) by using futures, swap and survey data to separate the unexpected component of the announcement, and found the negative and significant response. Unlike Bohl et al. [19] who studied with daily data, Hussain [59] analyzes the reaction of European stock market to the monetary policy announcements with the high frequency 5-minute data and found significant response as well.

The impact of economic news (monetary policy and macroeconomic) on stock market is investigated in terms of different criteria causing an asymmetric effect, such as whether the news is good or bad [18, 24, 50, 51, 67, 68, 74, 75, 81, 88, 99], whether the market is bull or bear [12, 70]. Basistha and Kurov [12] found that unexpected policy rate changes affect the stock returns much more in recession and tight monetary policy conditions.

2.2. Effect of Macroeconomic Announcements on Stock Returns

The relationship between economic announcements and stock market is examined by many economists. The employment, CPI and PPI report announcements are the most studied ones among the macroeconomic news. Feldstein [46] and Summers [96] advocates that there is a negative association between inflation and stock prices since higher inflation reduces real after-tax profits due to the non-indexation of inventory and depreciation charges.

As an earlier study, which investigates the effects of periodic announcements on stock market, Pearce and Roley [85] used weekly money announcements, separated the changes as anticipated and unanticipated, and found that only unanticipated money supply changes effect stock prices confirming efficient market hypothesis. For the same sample period model, Pearce and Roley [86] examined inflation, real economic activity, and discount rate announcements in addition to money stock announcements. They found that expected part of the announcements does not affect the stock market consistent with the previous study. Specifically, for consumer price index (CPI) announcements, although daily stock market data was used in both of the study, Schwert [92] and Pearce and Roley [86] found different results: there was negative response of stock market to unexpected CPI announcements in the former but no significant response in the latter one. Jain [61] explained this difference with the frequency of the stock market data and examine the announcement effect with hourly return data. Although Jain [61] used the same announcement and expectation data with Pearce and Roley [86], the effect of CPI announcements was significant and negative on stock prices. This is the very beginning of understanding the importance of using higher frequency data set for economic announcement effects on stock market, however daily data will continue to be used in stock market volatility analyses. For both daily and intraday data usage, ARCH/GARCH models, which introduced by Engle [37] and Bollerslev [20] are mostly preferred for the volatility forecasting.

2.2.1. Effect of Inflation Rate Announcements on Stock Return Volatility

Graham et al. [53] and Nikkinen and Sahlström [83, 84] used various U.S macroeconomic news including unemployment rate, producer price index (PPI) and consumer price index (CPI) to examine the announcement effect on stock market volatility with regression models, also GARCH(1,1) is used to model the stock market volatility. Graham et al. [53] performed the analysis for the period between January 1995 and December 2001 and found that only the announcements important for stock valuation affect the stock market significantly and CPI did not influence implied volatility. However, it is stated that this result might be obtained since the separation of CPI from the other indices announced in the same report is not clear. Kim et al. [65] use the same type of macroeconomic news between January 1986 and December 1998 and could not find any impact of announcements on stock market volatility. In this study, high-frequency data will be used instead of daily data in order to eliminate this type of problems. In the studies of Nikkinen and Sahlström [83, 84], the volatility analyses are performed with the same type of data set (macroeconomic news announcements and FOMC meetings) and same sample period (January 1996 to December 2000), but the former examined the effects of U.S. news on U.S. stock market volatility and the latter examined both domestic and U.S. news on European (German and Finnish) stock market volatilities. Since the announcement date is scheduled and known by investors, both studies confirm that implied volatility increases just before and until the announcement day, and then it decreases after that day. The results also show that FOMC meetings have strong and significant effect on both U.S. and German and Finnish stock market volatilities.

Nikkinen et al. [82] expanded the related studies by examining impact of the same type of announcements on volatility of 35 different local stock market indices for the period between July 1995 and March 2002. GARCH modelling was used for the volatilities of each country's stock market and the regression analyses were performed for each region. According to the results, while CPI report is not significant in European countries, it significantly increases volatility in developed Asian countries and some emerging Asian countries. The significant effect of U.S. macroeconomic announcements on the local results stock market volatility of foreign countries are consistent with the earlier studies [64, 66].

Rangel [88] analyzed the impact of scheduled macroeconomic and federal funds rate announcements on volatility of stock market for U.S. by using GARCH model and Poisson jump process together, which is a different non-linear channel in the literature. The result showed that most of the announcements including CPI have a little effect on conditional volatility, and the significance of the impact gets more important when the unexpected component is included into the model. For all the news (excluding for PPI), the effects of shocks are significant and short-lived.

As one of the latest studies, in which the effects of U.S. macroeconomic announcements on local stock market volatility are investigated, Cakan et al. [27] uses GARCH model and found that volatility shocks are persistent and asymmetric on emerging stock markets.

Although, some economists use daily stock prices for announcement analyses on the stock market volatility since the data are easier to handle, some others prefer to use high-frequency data in order to eliminate some problems such as endogeneity and omitted variable issues [16, 17, 33, 45, 89]. Andersen et al. [8] examined effects of macroeconomic news on U.S., German and British stock market volatility with 5-minute data from January 1992 to December 2002 and used multivariate GARCH model. The results show that bad macroeconomic news increased the stock market volatility during contractions, but decreased the volatility during expansions. Therefore, the total effect can be misleading if the announcements are not separated as bad and good.

2.2.2. Effect of Interest Rate Announcements on Volatility

As macroeconomic announcements, the effects of monetary policy announcements on stock market volatility are examined in the literature. Monetary policy announcements are made regularly on scheduled days by monetary policymaking authorities, which are Federal Open Market Committee (FOMC) for U.S., the Governing Council of the European Central Bank (ECB) for euro area countries, and monetary policy committee of the Central Bank of Turkey (CBT) for Turkey. Thorbecke [98] investigates how the stock returns react to the announcement of FOMC, and shows that the effects of monetary policy are significant on ex-ante and ex-post stock returns, and tighter monetary policy reduces stock returns.

Among the economists using daily stock market data, Bomfim [24] examined the association between FOMC meetings and stock market volatility for the period June 1989 to December 1998 with a GARCH(1,1) process for volatility estimation. The results indicated that good news (higher federal funds rate than market expectations) increase the stock market volatility more than bad news in the short-run. This shows that leverage [18] and volatility-feedback [50] hypotheses are valid (see also [22, 39]). Bomfim [24] also indicated that an asymmetric effect of announcements on volatility (see also [18, 50, 81]) exists because the surprises in the policy boost the market volatility.

Bohl et al. [19] examined the effects of monetary policy announcements made by the ECB's Governing Council on four major European stock markets between January 1999 and February 2007 using one month EURIBOR rate as an interest rate proxy with the heteroscedasticity technique. The results showed that the reaction of the stock markets to policy shocks (unexpected rate change) is significant and negative in the short-run.

As an earlier study on the advantages of using intraday data, Andersen and Bollerslev [5, 6] states that standard time series models fail to capture the intraday seasonality of high frequency returns, and found the significant effect of monetary policy surprises on major European and the U.S. stock indices. The existence of the intraday seasonality is proven by Gürkaynak et al. [55] by checking the effects of monetary policy surprises on return and volatility. Andersson [9] found that target and path surprises cause and increase in intraday volatilities in Euro area and U.S. markets following their respective economies' monetary policy decisions. Farka [45] examines the effects of policy changes by Fed on the volatility of stock prices by using GARCH(1,1) model with 20-min intervals, found that the volatility increases during the policy announcements and declines after the release, and also the existence of asymmetric response of stock returns to the type of the policy. Lunde and Zebedee [76] investigates also the effects of FOMC announcements on the intraday volatilities of SP500 index with 15-minute data and found the similar results with Farka [45]. Chuliá et al. [28] uses the same methodology on individual stocks, and they found that the stocks respond to bad news more than good ones. Hussain [59] found the same response with Farka [45] and Lunde and Zebedee [76] for the European and U.S. stock indices and states that using intraday financial data enables to separate the effects of macroeconomic and monetary policy announcements on stock index returns and volatilities.

2.3. Effect of Macroeconomic Announcements on the Turkish Stock Market

The studies, which analyze the effects of economic announcements in Turkey, are very limited and have accelerated in recent years. Soylu et al. [95] investigated the effects of interest rate announcements in the scope of inflation targeting regime on BIST-30 Index, U.S. Dollar/TRY and EURO/TRY exchange rates, by using GARCH and EGARCH models with daily data. The results showed that the reaction in volatility changes according to the sign of the interest rate change. Erdoğan [42], who investigates the effect of economic announcements on BIST-100 Index volume and transaction volume of volatility by using TGARCH-M model, found that volume changes and volatility is affected by economic authorities. However, the announcements include the statements of CBT Chairman, FED Chairman, and the Republic of Turkey Minister of Economics, which are not periodic announcements. Gökalp [52] analyzed the effects of the policy interest rate decisions of CBT on the sector indices by using GMM technique with daily returns. The findings show that the effects change in terms of the different sectors. Belen and Gümrah [15] found that daily BIST-100 Index returns reacts to the inflation announcements but not systematically and particularly in the announcement day. However, the studies of Gökalp [52] and Belen and Gümrah [15] did not include volatility analyses.

CHAPTER 3

DATA AND DESCRIPTIVE STATISTICS

In this thesis, a two-stage methodology is used to investigate the announcement effects on volatility. First, the stock market volatility is estimated and forecasted by econometric models. Second, the effects of economic announcements on volatility are analyzed with the event study methodology. After the data for both of these stages are described in this chapter, the analyses are explained in detail in the next chapter.

3.1 Stock Price Data

The BIST-30 Index is a capitalization-weighted index composed of Turkish National Market companies from different sectors. The BIST-30 Index is chosen for the analyses because of its high transaction volume and depth. Intraday prices of the BIST-30 Index data are obtained from Borsa İstanbul Historic and Reference Data Platform for the sample period between June 11, 2013 and December 31, 2016. The BIST-30 price index is calculated every 10 seconds before November 30, 2015. After then, it is calculated every 1 second during the sessions and published simultaneously.

3.2. Announcement Data

The Central Bank of Turkey (CBT) adopted the full-fledged inflation targeting regime in January 2006. Under this regime, two main communication tools are used by the CBT: inflation and interest rate announcements. For the inflation announcements, quarterly inflation reports and monthly price development reports are published after the yearly inflation targets are determined by CBT's Monetary Policy Committee (MPC)[1]. In addition, the monthly consumer price index (CPI) is

[1] http://www.tcmb.gov.tr/wps/wcm/connect/TCMB+EN/TCMB+EN/Main+Menu/MONETARY+POLICY/PRICE+STABILITY/Inflation+Targets

announced by the Turkish Statistical Institute (TURKSTAT) on the third business day of each month at 10:00 for the sample period[2], and CBT publishes monthly price development reports within one working day following these announcements[3]. For the interest rate announcements, MPC meets to determine the policy rate every month on pre-announced dates[4], the decisions are publicized on the CBT website on the meeting day at 14:00, also the summary is published within the 5 working days on the website of CBT. In addition to the announcement of CBT, TURKSTAT also announces the interest rate decisions at 14:30 on the same day. Within the scope of this study, monthly CPI (annual rate of change (%)) announcements, and the monthly overnight (O/N) rate announcements are used for the analyses.

3.3. Sample Period

Trading hours at Borsa Istanbul were changed three times during the sample period as shown in Table 1. Since intraday volatilities are calculated, it is important to take into account these changes in the calculations.

Table 1. Continuous Trading Hours of Borsa Istanbul

	Morning Session		Afternoon Session	
Intervals	Opening	Closing	Opening	Closing
11.06.2013 - 18.11.2015	09:35	12:30	14:15	17:30
19.11.2015 - 25.03.2016	09:35	12:30	13:30	17:30

[2] http://www.turkstat.gov.tr/ingtakvim/tkvim.zul#tb1

[3] http://www.tcmb.gov.tr/wps/wcm/connect/TCMB+EN/TCMB+EN/Main+Menu/PUBLICATIONS/Reports/Monthly+Price+Developments

[4] http://www.tcmb.gov.tr/wps/wcm/connect/TCMB+EN/TCMB+EN/Main+Menu/MONETARY+POLICY/Monetary+Policy+Committee/2006

Table 1. (continued)

	Morning Session		Afternoon Session	
Intervals	Opening	Closing	Opening	Closing
28.03.2016 - 11.11.2016	09:35	13:00	14:00	17:30
14.11.2016 - present	10:00	13:00	14:00	18:00

3.4. Descriptive Statistics

Rahman et al. [87] state that instead of absolute price movements, using percentage change in prices (rates of return) is more appropriate to measure the effects of announcements on volatility. Returns are calculated as $r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \times 100$, where p_t is the BIST-30 index value at time t and p_{t-1} is the BIST-30 index value at time $t-1$. Figure 1 presents the BIST-30 index values during the sample period. A first glance at Figure 1 suggests that the volatility of the index decreases during 2016.

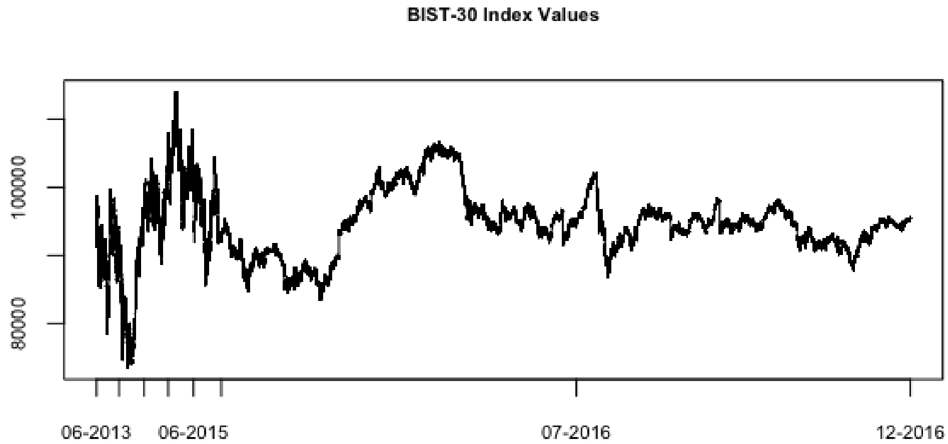


Figure 1. BIST-30 price index values for the sample period June 2013 to December 2016

As described in the next section, the volatility of the BIST-30 index is modeled by using 5-minute returns calculated for the index. These 5-minute returns are also used to test the macroeconomic announcement effects. Figure 2 presents the 5-minute return series during the sample period. As can be seen in the figure, there are several extreme volatility episodes during the sample period and these need to be addressed in the econometric models used for estimating the return volatilities.

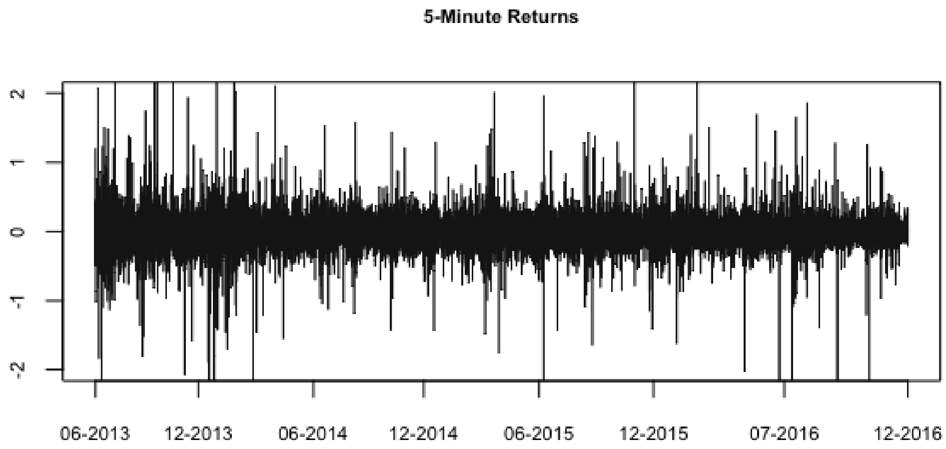


Figure 2. BIST-30 5-minute returns for the sample period June 2013 to December 2016

The use of high-frequency data, by its nature, provides a better opportunity to examine the reaction of stock markets to the announcements by eliminating the endogeneity and omitted variables as explained in the previous chapter.

3.4.1. Characteristics of the Return Series

Before modeling the volatility of the BIST-30 index, it is necessary to learn about the distributional characteristics of the return series in order to decide whether a GARCH-family methodology would be appropriate to use with the data chosen for the thesis. The following section describes the characteristics of the return series:

STATIONARITY: Although the asset prices are not stationary, return series typically fluctuates around a constant mean [97]. 5-minute returns of the BIST-30 Index are tested for stationarity during the sample period. For this purpose, the Augmented Dickey-Fuller Test and the Kwiatkowski–Phillips–

Schmidt–Shin (KPSS) Test are used. The Augmented Dickey-Fuller Test has the following hypotheses:

$$H_0\text{: Unit root exists (The data are not stationary),}$$

$$H_1\text{: Unit root does not exist (The data are stationary).}$$

For the 5-minute return series, the null hypothesis is rejected with at an alpha level of 1 percent, since p-value is smaller than 2.2e-16. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test has the following hypotheses:

$$H_0\text{: The data are stationary,}$$

$$H_1\text{: The data are not stationary.}$$

For both the level and the trend stationarity tests, the null hypothesis cannot be rejected at an alpha level of 5 percent with p-value 0.1. Therefore, the results of both tests imply that the returns are stationary and that they are not random walks. This finding means that the GARCH-family methodologies would be appropriate to use for modeling the data on hand.

VOLATILITY CLUSTERING: As first described by Mandelbrot [77], volatility clustering means that "… large changes tend to be followed by large changes -of either sign- and small changes tend to be followed by small changes…". In Figure 3, volatility clustering can be detected visually, and the autocorrelation function of squared returns can be used to capture this behavior of financial series [29], since the correlation coefficient is a measure of linear dependence. Figure 3 is prepared with the data of randomly selected five days for the purpose of better illustration.

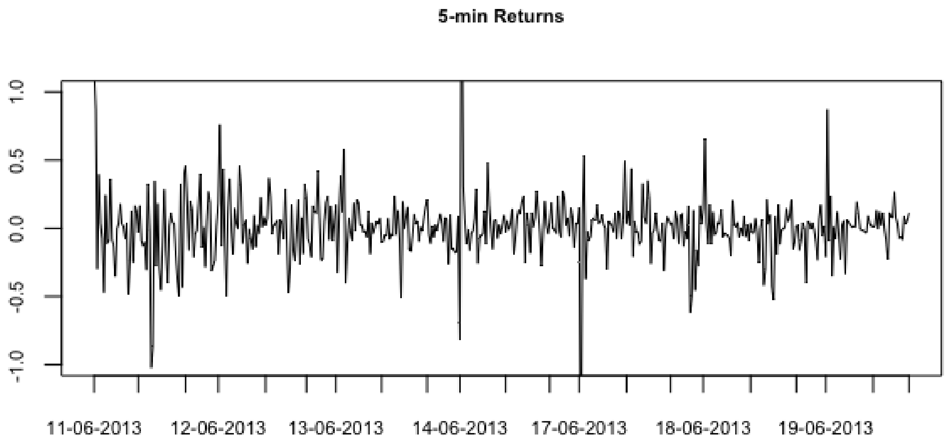


Figure 3. 5-min returns for the illustration of volatility clustering

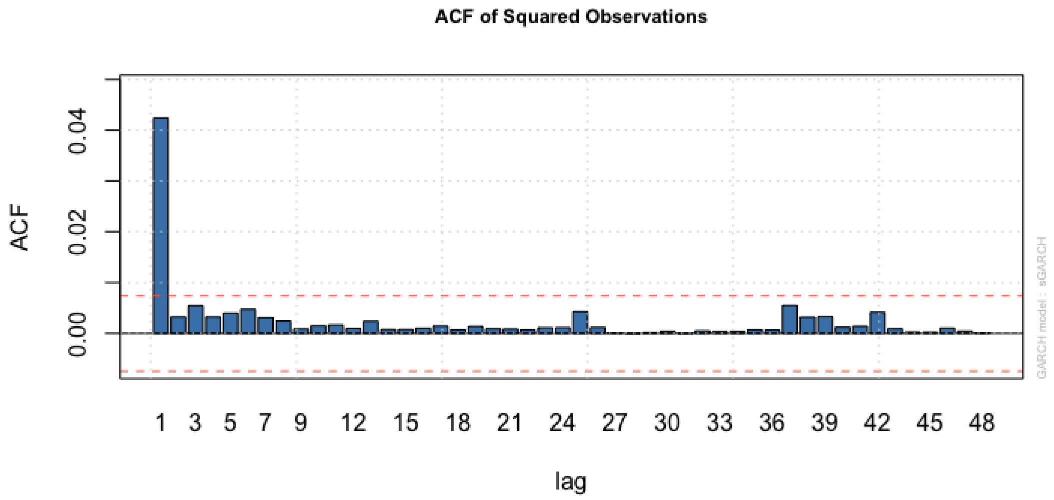
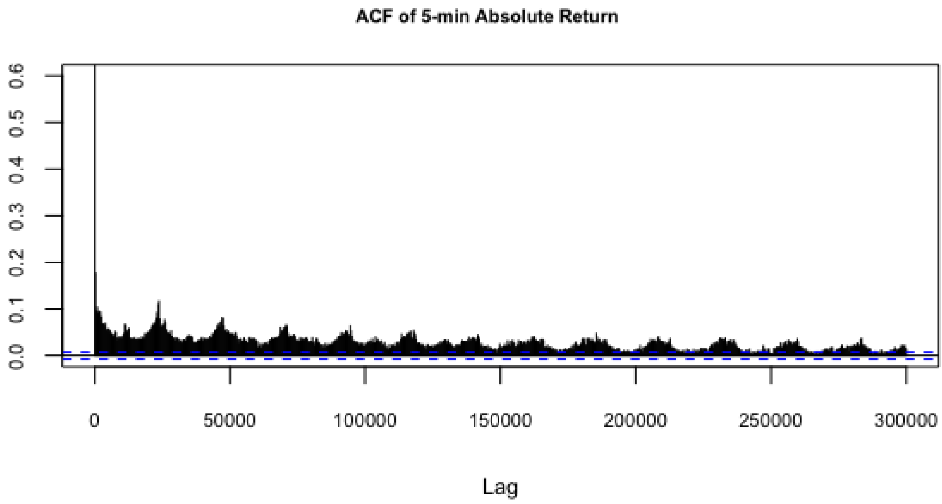


Figure 4. Autocorrelation function of squared returns



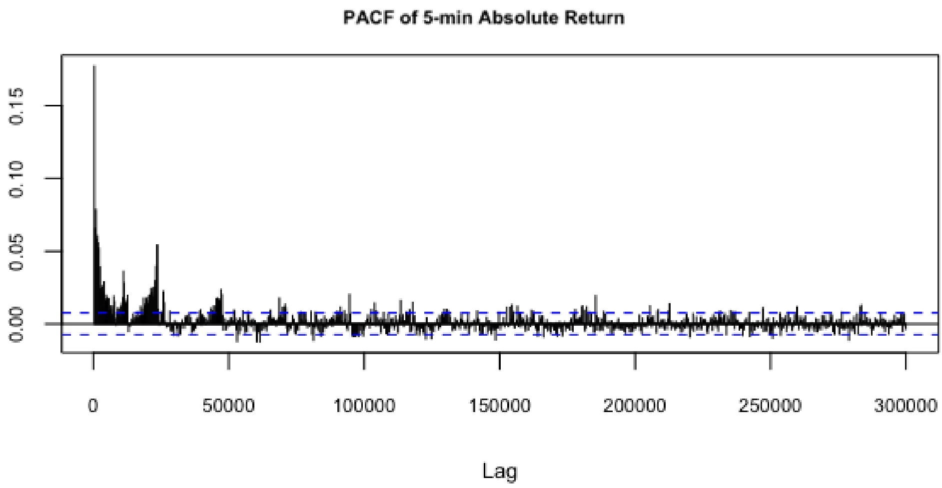


Figure 5. ACF and PACF of 5-minute returns

The two dashed horizontal lines are the bounds for the 95% confidence interval for the autocorrelation function. As seen in the autocorrelation and partial autocorrelation function plots presented in Figures 4 and 5, there is significant autocorrelation in the squared as well as absolute returns, implying that returns at different times are not independent of each other, which is a characteristic of long memory processes.

In addition to the autocorrelation plots, Ljung-Box test is used in order to test the randomness of returns. Since the Ljung-Box test is an overall test for lack of fit in autoregressive-moving average models based on a number of lags, it is referred to as a portmanteau test:

H_0: The return series is strict white noise processes,

H_1: There is a serial autocorrelation in the return series.

The null hypothesis is rejected with small p-values (smaller than 2.2e-16) for both returns and squared returns, meaning that the return series is not independent of each other over time at an alpha level of 1 percent.

However, even if the return series is uncorrelated, serial dependency in squared return series can still exist due to a dynamic conditional variance process, which implies conditional heteroscedasticity. The existence of volatility clustering is evidenced in this case, and this feature of return series is modelled by Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) type models. ARCH-LM Test [37] is used to assess the significance of the ARCH effect:

H_0: ARCH effect does not exist,

H_1: ARCH effect exists.

Small p-value (2.2e-16) obtained from the ARCH-LM test, for the number of lags 10, indicates that there is an ARCH effect in the return series, which means that the return series has a heteroscedasticity effect.

With the results of both tests, it is obvious that GARCH-type models can be applied to BIST-30 Index returns.

SLOWLY DECAYING AUTOCORRELATION FUNCTION: This is also a common feature for return series, which suggests that the errors can be described with GARCH models. Since there exists a decay of successive lags in Figure 4, this means that there is substantial evidence of a conditionally heteroscedastic process.

TAYLOR EFFECT: The heteroscedasticity behavior of financial return series can be justified by the autocorrelations in the powers of the absolute values of returns [73]:

$$C_\delta = corr\left(|r_{t+h}|^\delta + |r_t|^\delta\right), \qquad h = 1,2, \ldots$$

Absolute returns have significant serial correlation over long lags, and also autocorrelations of absolute returns are greater than those of squared returns [97]. According to this effect, the autocorrelations of absolute returns to the power of δ is maximized at $\delta = 1$. As seen in Figure 6, the autocorrelations are positive for each lag and usually reach their maximums at the same value around $\delta = 1$.

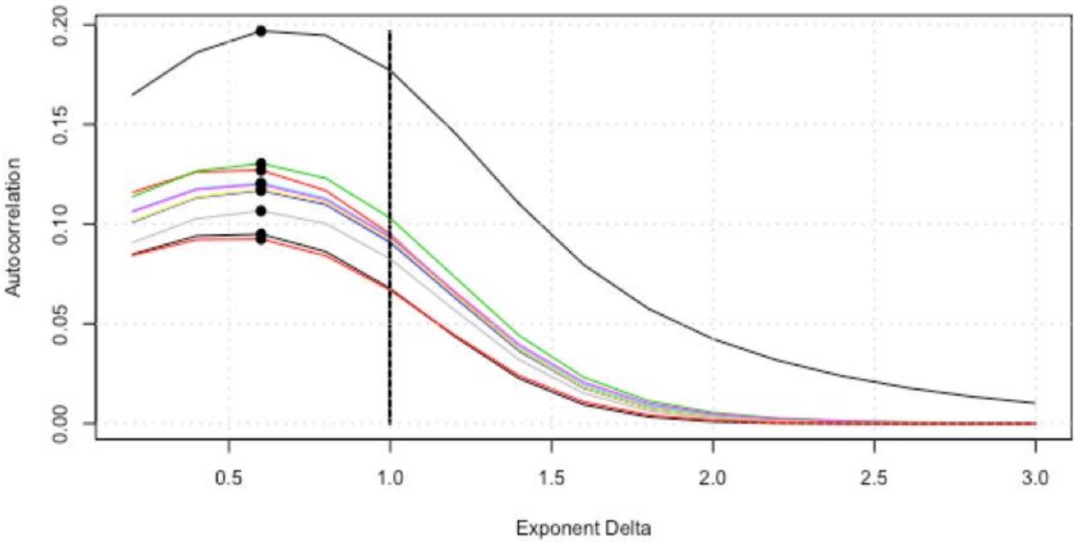


Figure 6. Taylor effect for 5-minute returns where it is shown that ACF between $|r_t|^\delta$ and $|r_{t+h}|^\delta$ for $1 \leq h \leq 10$

NON-NORMALITY (HEAVY TAILS):

The return series have mean 0, as seen in Table 2, but they do not have normal distribution.

In order to test the normality of return series, two tests are applied: Jarque-Bera Test and Anderson-Darling Normality Test. For both of the tests, null and alternative hypotheses are the same.

$$H_0\text{: The data are normal with skewness 0 and kurtosis 3,}$$

$$H_1\text{: The data are not normal.}$$

Normality of the residuals is rejected at the 1% significance level since the p-values for both tests are very small (< 2.2e-16), implying the return series are not normal, which is one of the characteristics of financial return data.

Table 2. 5-Minute Return Summary

5-Minute Return Summary	
Minimum	-8.7783
1st Quantile	-0.0627
Median	0.0017
Mean	0.0000
3rd Quantile	0.0648
Maximum	5.2794
Skewness	-2.2660
Kurtosis	218.3024

SKEWNESS: The distribution of returns is often negatively skewed, meaning financial markets respond more strongly to negative news. For the sample period between June 2013 and December 2016, skewness is -2.2660, which implies that the probability of earning negative returns is higher than earning positive returns.

3.4.2. Intraday Data Characteristics

DIURNAL (PERIODIC) PATTERNS: The diurnal volatility patterns observed at the beginning and the end of the trading sessions for BIST-30 can be seen in Figures 7 and 8. These figures show that each day exhibits a pattern with higher volatility at the openings and closings of the morning and afternoon sessions. Figure 8 is prepared with the data of randomly selected five days for the purpose of better illustration.

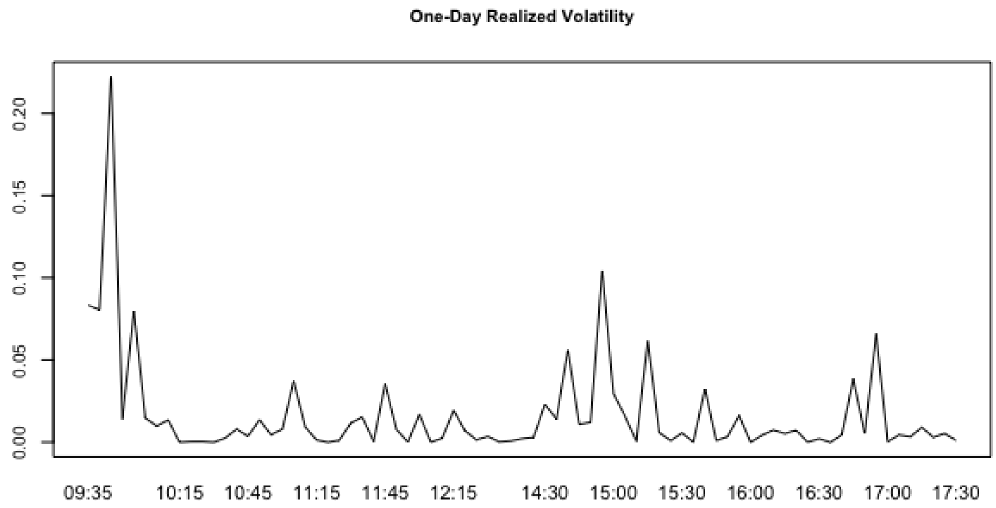


Figure 7. One-day realized volatility for the illustration of diurnal pattern

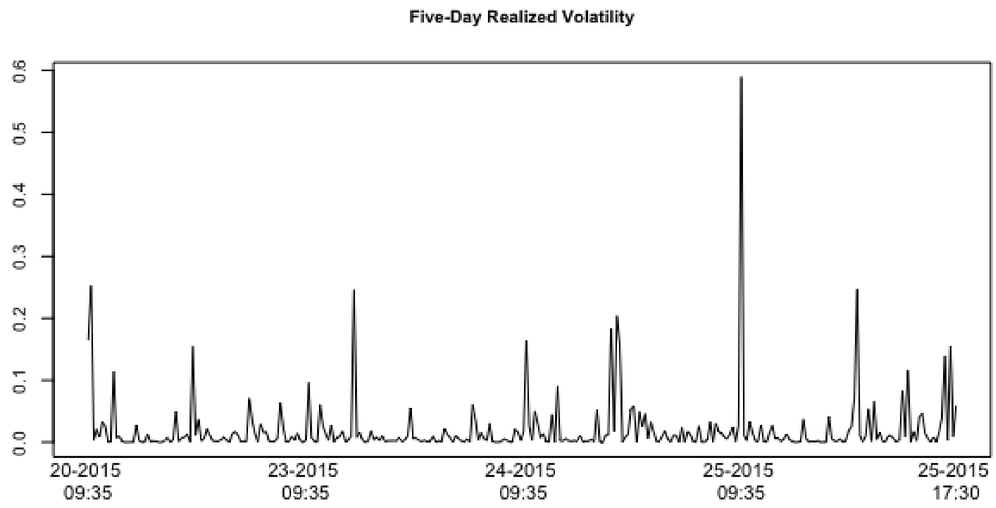


Figure 8. Five-day realized volatility for illustration of diurnal pattern

EXCESS KURTOSIS: The distribution of X_t is leptokurtic if it has fatter tails than the normal distribution, meaning it has excess kurtosis. This behavior is well known for financial markets, particularly in high-frequency data. The kurtosis of 5-minute return data for the sample period is 218.3024, which is much larger than 3, the kurtosis value of normal distribution. The high kurtosis value indicates that there are extreme movements between the transaction prices over the sample period.

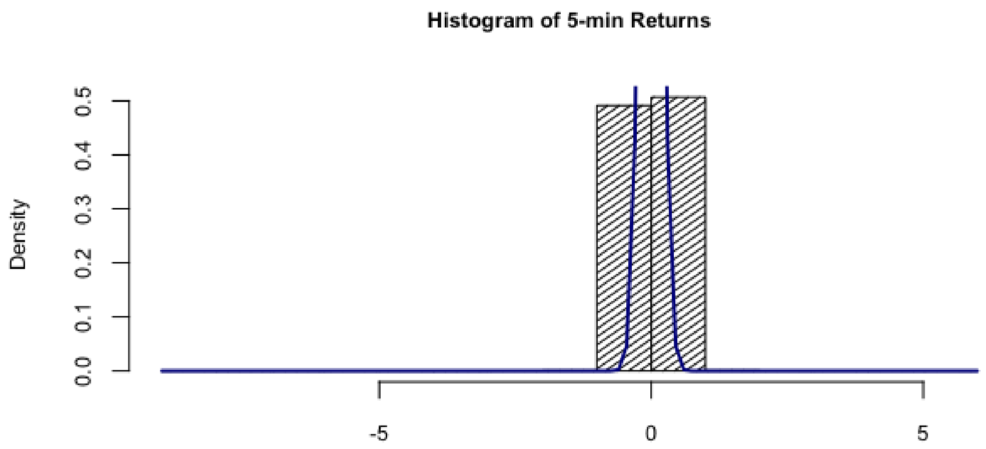


Figure 9. Histogram of 5-minute returns

CHAPTER 4

METHODOLOGY AND MODEL CONSTRUCTION

4.1. Financial Modelling Methodology

As stated in the report of London Government Office for Science [14], high frequency computer based trading (HFT) has been growing with the technological developments in financial markets for the last decade in U.K. and U.S., and the price volatility is an important measure for financial stability. The level of HFT in BIST, as an emerging market, has been investigated and by Ersan and Ekinci [44], and they found that approximately 6% of the orders belongs to HFT. Also, the ratio gets higher in case of large order, after BIST improved its order submission platform and reduced tick size for certain stocks [44]. Therefore, with growing HFT, intraday volatility estimation is getting more substantial for the investors, and micro-level price modelling is a hot topic for the financial econometrics literature. In this thesis, modelling and forecasting high-frequency volatility is applied to analyze the intraday effect of announcements the on volatility of BIST. The data used in this process are ‘‘ultra-high frequency (UHF) data” (a name given by Engle [38]), also known as tick-by-tick data or transaction data.

By using transaction data, one could model intraday volatility with different methods. First, the irregular price and return data can be used directly. After returns are adjusted with division by duration between two trade events, which is modelled by autoregressive conditional duration (ACD) introduced by Engle and Russell [40], UHF-GARCH model [38, 43] can be applied. Second, irregular spaced transaction prices can be converted to regularly spaced prices, such as 5-minute data used in this thesis. Although there is a loss of information after this conversion process, modeling of the volatility becomes easier. Two modelling options used in this thesis will be explained in the next part: conventional GARCH model and multiplicative component GARCH model.

4.1.1. GARCH Model

For forecasting volatility, Generalized Autoregressive Conditionally Heteroscedastic (GARCH) models originated by Engle [37] are used in the finance literature. The key concept is that the variance of a time series of returns is conditional on its past values. Before the multiplicative component GARCH model is offered, conventional GARCH(1,1) model was accepted as the best for intraday volatility estimations among the other applied models according to Akgiray [3], Rahman et al. [87], Tian and Guo [99].

In the conventional GARCH(p,q) model, there are two main components: the mean model and the variance model. The variance model is defined as follows:

$$X_t = \sqrt{h_t}\varepsilon_t, \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i X_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}, \tag{2}$$

where

X_t: stationary time series,

ε_t: innovation or shock, discrete white noise $\sim N(0,1)$,

h_t: current time conditional variance,

h_{t-j}: previous time conditional variance,

α: The effect of past observation to the market volatility (ARCH term),

β: The effect of past volatility to the market volatility (GARCH term),

$\alpha_0 > 0$, $\alpha_i, \beta_i \geq 0$, and $\sum_{i=1}^{\max(p,q)}(\alpha_i + \beta_i) < 1$.

If β_j gets closer to 1, it means that there is a persistent effect of a shock on volatility in the long run. If α_i gets larger, then the volatility becomes more vulnerable to shocks in the short run.

The conditional variance concept offered by the GARCH model makes it possible to capture the main stylized facts characterizing financial series as stated in the book of Francq and Zakoian [47] on page 19, such as volatility clustering, excess kurtosis, slowly decaying autocorrelation function, negative skewness, and Taylor effect.

The simplest form of GARCH (1,1) model for return series can be expressed as follows:

$$X_t = \sqrt{h_t}\varepsilon_t, \tag{3}$$

$$h_t = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1}. \tag{4}$$

Properties of GARCH (1,1):

$$X_t = \varepsilon_t \sqrt{\alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1}}. \tag{5}$$

Let $\eta_t = X_t^2 - h_t$ and $h_t \; = X_t^2 - \eta_t$. If the model is rewritten:

$$X_t^2 = \alpha_0 + (\alpha_1 + \beta_1)X_{t-1}^2 + \eta_t - \beta_1 \eta_{t-1}. \tag{6}$$

Therefore, h_t is the forecast of u_t^2, and η_t is the white noise $\sim N(0,1)$.

Let $\mathcal{F}_{t-1}$ be the information set available at time $t-1$, which can be called as $\sigma - algebras\ of\ events\ up\ to\ time\ t-1$, [72], such as $\mathcal{F}$: $\mathcal{F}_0, \mathcal{F}_1, \dots, \mathcal{F}_{t-1}$ and the last information that we have is at time $t-1$.

- Conditional Mean:

$$\mathbb{E}(X_t|\mathcal{F}_{t-1}) = \mathbb{E}\left(\varepsilon_t\sqrt{\alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1}}\,\middle|\mathcal{F}_{t-1}\right)$$
$$= \mathbb{E}(\varepsilon_t|\mathcal{F}_{t-1})\sqrt{\alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1}} = 0. \quad (7)$$

- Unconditional Mean:

$$\mathbb{E}(X_t) = \mathbb{E}(\mathbb{E}(X_t|\mathcal{F}_{t-1})\,) = \mathbb{E}(0) = 0. \quad (8)$$

Therefore, mean of X_t is zero.

- Conditional Variance:

$$Var(X_t|\mathcal{F}_{t-1}) = \mathbb{E}(X_t^2|\mathcal{F}_{t-1}) - \underbrace{\left(\mathbb{E}(X_t|\mathcal{F}_{t-1})\right)^2}_{\approx 0^2}$$
$$= \mathbb{E}(h_t\varepsilon_t^2|\mathcal{F}_{t-1})$$
$$= \mathbb{E}(\varepsilon_t^2|\mathcal{F}_{t-1})\mathbb{E}(\alpha_0 + \alpha_1 X_{t-1}^2$$
$$+ \beta_1 h_{t-1}|\mathcal{F}_{t-1}) - 0$$
$$= \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 h_{t-1} = \sigma_t^2. \quad (9)$$

- Unconditional Variance:

X_t is conditional heteroscedastic,

$$Var(X_t) = \mathbb{E}(X_t^2) = \mathbb{E}[\alpha_0 + (\alpha_1 + \beta_1)X_{t-1}^2 + \eta_t - \beta_1\eta_{t-1}]$$
$$= \alpha_0 + (\alpha_1 + \beta_1)\mathbb{E}(X_{t-1}^2) = \frac{a_o}{1 - (\alpha_1 + \beta_1)}. \quad (10)$$

Since $Var(X_t) > 0$, $1 - (\alpha_1 + \beta_1)$ should be greater than 0, therefore, $\alpha_1 + \beta_1 < 1$.

- GARCH(1,1) process is a covariance-stationary white noise process with $\alpha_1 + \beta_1 < 1$.

- Conditional Density:

$$f(X_t|\mathcal{F}_{t-1}) = \sigma_t f(\varepsilon_t|\mathcal{F}_{t-1}) = \sigma_t . N(0,1) \sim N(0, \sigma_t^2).$$

- Volatility Clustering: The GARCH(1,1) model has an ability to capture this behavior. As seen in Equation (4), when X_{t-1} or h_{t-1} is large, σ_t^2 also gets larger.

- The distribution of X_t is leptokurtic, has fatter tails than normal distribution, meaning it has excess kurtosis:

$$\frac{\mathbb{E}(X_t^4)}{[\mathbb{E}(X_t^2)]^2} = \frac{3[1-(\alpha_1+\beta_1)^2]}{1-(\alpha_1+\beta_1)^2-2\alpha_1^2} > 3, \tag{11}$$

  where $1-(\alpha_1+\beta_1)^2-2\alpha_1^2 > 0$.

4.1.2. Multiplicative Component GARCH Model

Conventional GARCH models are not sufficient for intraday volatility estimation because of the diurnal patterns of volatility and trading activity [41]. The diurnal volatility pattern of BIST-30 is illustrated in Figures 7 and 8.

Although Nelson [81] tried to take into account diurnal patterns by making adjustments, their methodology could not capture the whole intraday patterns. Engle and Sokalska [41] offers multiplicative component GARCH model built on the work of Andersen and Bollerslev [5, 6], which expresses the conditional volatility as a multiplication of daily, diurnal, and stochastic intraday volatility components.

First of all, let us define the continuously compounded intraday return series for this thesis as:

$$r_{t,i} = \ln\left(\frac{P_{t,i}}{P_{t,i-1}}\right), \tag{12}$$

where t represents days, i represents 5-minute intervals within one day, $P_{t,i}$ refers the price of BIST-30 at the end of i^{th} 5-minute interval of day t.

According to the multiplicative component GARCH model, intraday return series can be expressed as follows:

$$r_{t,i} = \sqrt{h_t s_i q_{t,i}}\varepsilon_{t,i}, \tag{13}$$

where

h_t is the daily exogenously determined forecast variance component,

s_i is the diurnal (calendar) variance pattern,

$q_{t,i}$ is the stochastic intraday variance component, with $\mathbb{E}(q_{t,i}) = 1$

$\varepsilon_{t,i}$ is an error term (innovation) $\sim N(0,1)$.

Let define each component h_t, s_i, and $q_{t,i}$, respectively.

- The daily variance component can be forecasted by daily GARCH, multifactor models or daily realized variance [41]. In this thesis, forecasted volatility h_t is derived from a daily GARCH model. EGARCH model is selected and the reasons are detailed in the next part.

$$X_t = \sqrt{h_t}\varepsilon_t, \tag{14}$$

$$\ln(h_t) = \alpha_0 + \alpha_1\big(|\varepsilon_{t-1}| - \mathbb{E}(|\varepsilon_{t-1}|)\big) + \gamma\varepsilon_{t-1} + \beta_1 \ln(h_{t-1}), \tag{15}$$

  where $\varepsilon_t \sim i.i.d. N(0,1)$.

- With the assumptions that intraday returns are serially uncorrelated, and the daily conditional variance is the sum of the variances in each interval, the diurnal variance pattern is calculated as:

$$\frac{r_{t,i}^2}{h_t} = s_i q_{t,i} \varepsilon_{t,i}^2, \tag{16}$$

$$\mathbb{E}\left(\frac{r_{t,i}^2}{h_t}\right) = s_i \mathbb{E}(q_{t,i}) = s_i, \tag{17}$$

$$s_i = \frac{1}{T}\sum_{t=1}^{T} \frac{r_{t,i}^2}{h_t}. \tag{18}$$

- The last component, $q_{t,i}$, is the residual volatility modelled by GARCH(1,1) process. First, in order to work with a stationary return series, intraday return series, $r_{t,i}$, should be normalized by dividing the daily component and the diurnal volatility component in order to proceed with the Equations (3) and (4):

$$\frac{r_{t,i}}{\sqrt{h_t s_i}} = \sqrt{q_{t,i}}\varepsilon_{t,i}, \tag{19}$$

where $\mathrm{r}_{t,i}/\sqrt{h_t s_i}|\mathcal{F}_{t,i-1} \sim N(0, q_{t,i})$.

Next, the stochastic intraday variance component is defined as:

$$q_{t,i} = \omega + \alpha\left(\frac{r_{t,i-1}}{\sqrt{h_t s_{i-1}}}\right)^2 + \beta q_{t,i-1}. \tag{20}$$

Standard GARCH(1,1) is chosen for the stochastic variance component, since it is shown to be an adequate specification and one of the most popular models as stated by Engle and Sokalska [41]. Therefore, the model is expressed by *mcsGARCH* model from now on.

4.1.2.1. Daily Variance Component Model Selection

The EGARCH model overcomes some limitations of the standard GARCH model. First, it allows an asymmetric effect between positive and negative innovation with the weighted innovation written as follows:

$$g(\varepsilon_t) = \gamma\varepsilon_t + \theta\big(|\varepsilon_t| - \mathbb{E}(|\varepsilon_t|)\big), \tag{21}$$

where θ and γ are real constants, ε_t and $|\varepsilon_t| - \mathbb{E}(|\varepsilon_t|)$ are i.i.d. with mean zero and continuous distribution, $\mathbb{E}\big(g(\varepsilon_t)\big) = 0$.

Let us see the asymmetry of $g(\varepsilon_t)$:

$$g(\varepsilon_t) = \begin{cases} (\gamma + \theta)\varepsilon_t - \theta\mathbb{E}(|\varepsilon_t|), & if\ \varepsilon_t \geq 0, \\ (\gamma - \theta)\varepsilon_t - \theta\mathbb{E}(|\varepsilon_t|), & if\ \varepsilon_t < 0. \end{cases}$$

Both model captures volatility clustering; however, the EGARCH model considers the effect of the direction of unanticipated excess return on volatility as seen in Figure 10.

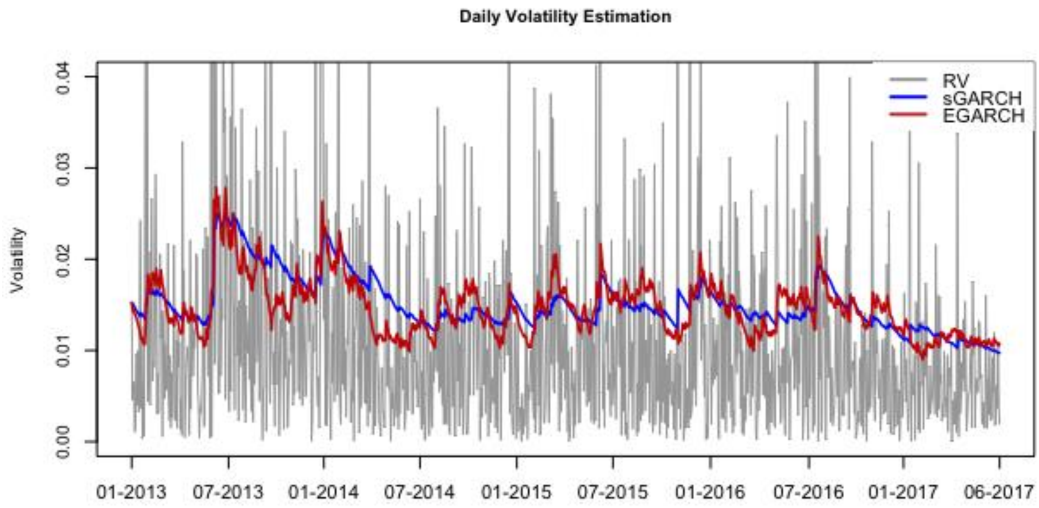


Figure 10. Comparison between sGARCH and EGARCH vs realized volatility

The sGARCH and EGARCH models are compared based on parameter estimations, information criteria, log likelihood values and errors as seen in Tables 3, 4 and 5 respectively. As an evaluation of errors, mean absolute error (MAE) and root mean squared error (RMSE) terms, which measure the difference between the realized volatilities and the estimated volatilities obtained by the models, are used. According to the results, the EGARCH model has better parameter estimations with lower p-values, lower information criteria, higher log likelihood values and smaller error terms. All of these imply that the EGARCH model is more preferable than the sGARCH model.

Table 3. sGARCH vs. EGARCH - Parameter Estimation for the Daily Variance

Parameter	Estimation	Std. Error	t-Value	p-Value
		Standard GARCH(1,1)		
ω	0.0000	0.0000	1.4667	0.1425
α	0.0661	0.0117	5.6590	0.0000
β	0.9199	0.0169	54.3655	0.0000
		Exponential GARCH(1,1)		
ω	-0.2466	0.0159	-15.4698	0.0000
α	-0.0700	0.0116	-6.0195	0.0000
β	0.96999	0.0020	492.5627	0.0000
γ	0.1503	0.0207	7.2425	0.0000

Table 4. sGARCH vs. EGARCH - Information Criteria for the Daily Variance

Information Criteria	Standard GARCH(1,1)	Exponential GARCH(1,1)
AIC	-5.4034	-5.4121
BIC	-5.3899	-5.3947
SIC	-5.4034	-5.4121
HQIC	-5.3985	-5.4058

Table 5. sGARCH vs. EGARCH – Evaluation Metrics for the Daily Variance

	Standard GARCH(1,1)	Exponential GARCH(1,1)
Log Likelihood	8503.794	8519.467
MAE	0.2632e-3	0.2546e-3
RMSE	0.6049e-3	0.5999e-3

4.1.2.2. Marginal Distribution of Innovation Selection

As a conditional density to use for the innovations, normal distribution, which is widely used in the literature, is not sufficient to capture stylized facts characterizing financial return series, such as volatility clustering, negative skewness and excess kurtosis in the conditional distribution [58, 69]. However, the normal inverse Gaussian Levy process (NIG-Lévy Process) by Barndorff-Neilsen [10], which is a subclass of the general hyperbolic distribution, provides a very good fit to the logarithmic stock returns [69]. Jensen and Lunde [62] state that NIG class of models allow to capture the stylized fact of volatility clustering and skewness.

The characteristic function of NIG- Lévy Process is expressed as follows:

$$\phi_{NIG}(x\colon \alpha, \beta, \mu, \delta) = e^{\delta\left(\sqrt{\alpha^2-\beta^2}-\sqrt{\alpha^2-(\beta+ix)^2}\right)+\mu ix}. \tag{22}$$

The probability density of NIG- Lévy Process is expressed as follows:

$$f_{NIG}(x\colon \alpha, \beta, \mu, \delta) = \frac{\alpha\delta}{\pi} e^{\delta(\alpha^2-\beta^2)^{\frac{1}{2}}-\beta(x-\mu)} K_1\left(\frac{\alpha(\delta^2+(x-\mu)^2)^{\frac{1}{2}}}{(\delta^2+(x-\mu)^2)^{\frac{1}{2}}}\right), \tag{23}$$

$$K_1(x) = \frac{1}{4}\int_0^\infty e^{t+\frac{y^2}{4t}} t^{-2} dt, \tag{24}$$

where $x, \mu \in \mathbb{R}$, $\alpha, \delta > 0$, $\beta \geq 0$,

α is tail heaviness,

β is the symmetry parameter,

μ is the location parameter,

δ is the scale parameter,

$K_j(x)$ is a modified Bessel function.

As seen in Equations (22), (23) and (24), NIG-Levy Process contains the parameters for heavy tails (α), skewness (β), excess kurtosis (δ), and jumps (μ).

4.2. Event Study Methodology

4.2.1. Determination of Event Windows

After the transition to the explicit inflation targeting regime, CBT makes two announcements every month: inflation rate and interest rate. It is observed that the stock market reacts to these announcements as in Figure 11.

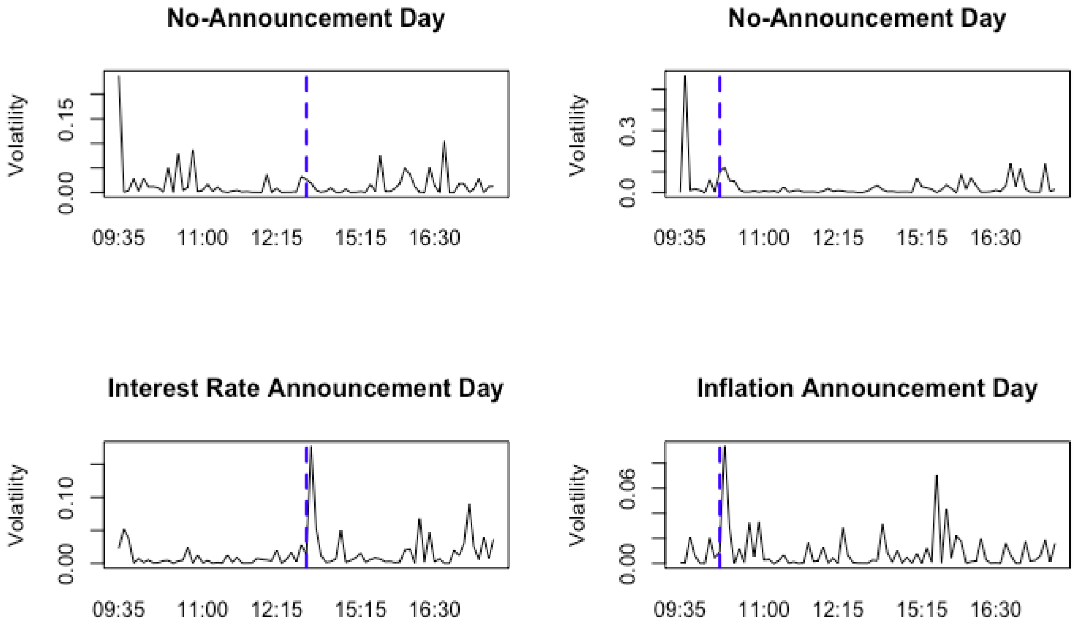


Figure 11. Announcement effects

Note: No announcement days are the same week-days of the corresponding announcements.

As an assumption of market expectations, the market -as represented by the BIST-30 Index- is expected to start adjusting itself 3 days before the announcement days and continue to adjust until 1 day after [23]. Including the announcement day, this 5-day time frame is defined as the “event window” and the announcement effect is investigated during this window. After determining the event windows for each interest and inflation rate announcement that took place during the sample period, the remaining days in between the event windows are defined as the “clear windows” or “estimation windows”. These estimation windows are assumed to be free from any macroeconomic announcement effects and they are used to estimate the stock market's volatility during “normal times”. The event study cycle is given in Figure 12.

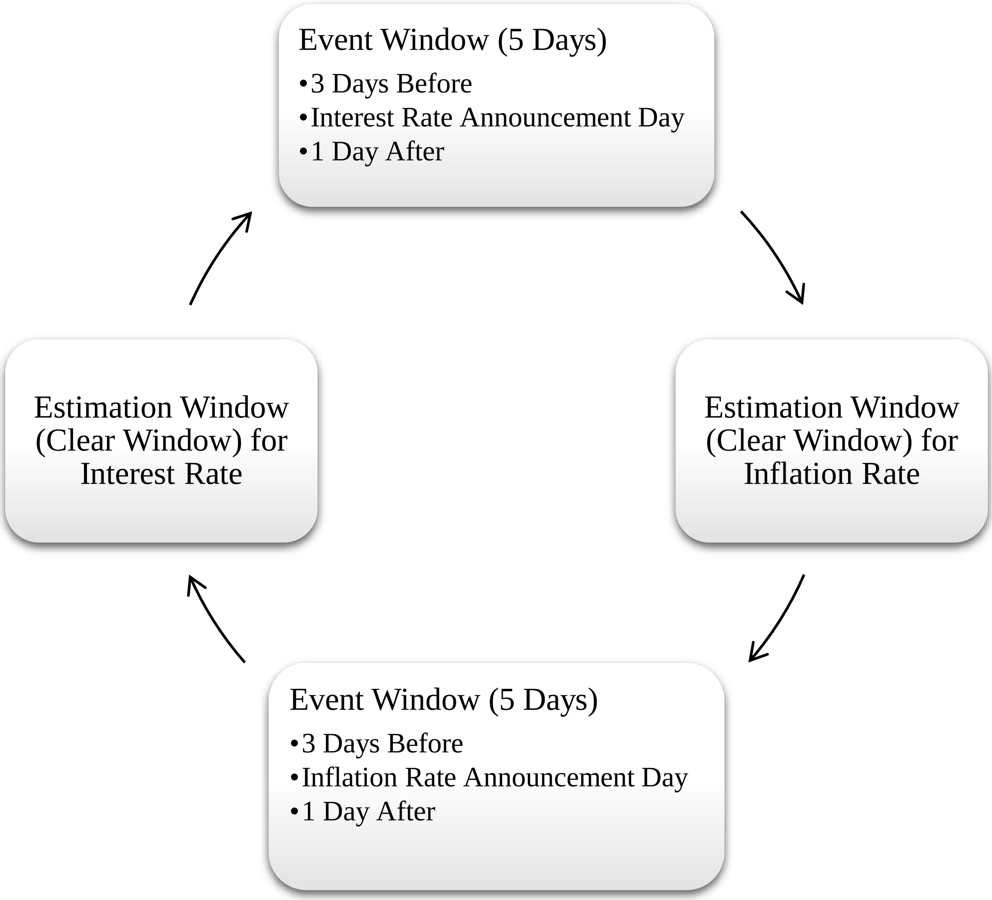


Figure 12. Modelling and forecasting cycle

After intraday volatilities for each event windows are forecasted, one sided t-test is used to test whether the ratio of realized intraday volatility to the corresponding forecasted intraday volatility (obtained from the mcsGARCH model) is significantly different from 1.0. The ratios are tested separately for each of the inflation and interest rate announcements. Both the realized and the forecasted volatilities are calculated based on the BIST-30 Index valued samples at regular intervals of 5 minutes during the trading days. For the test statistics regarding the volatility ratios, if the p-value is smaller than 0.05, meaning the volatility ratio is higher than 1, this indicates that the realized volatility is higher than the forecasted volatility. This is the case that implies that there is a significant reaction in the stock market following the announcement.

Robustness Check

As a robustness check, one more volatility ratio is calculated between the realized intraday volatilities and the corresponding average intraday volatilities. Average intraday volatilities are obtained by the mean of 5-minute realized volatilities on the same weekdays and same times but on non-announcement days.

For the sake of accuracy of intraday estimations, the estimation and event windows containing days from two different intervals are excluded from the analysis. The list of interest and inflation rate announcements included in modelling and analyses are given in Appendix. The total number of interest and inflation rate announcements included in the analyses is 39 and 35, respectively.

4.2.2. Announcement Effect Analyses on Volatility

Volatility is modeled by using the mcsGARCH model for each estimation window. Next, 5-day volatility forecasts are generated and compared with the realized volatilities during the relevant event window. This process is performed for each interest and inflation rate announcement separately. As a result, 39 different models are estimated for interest rate announcements and 35 different models are estimated for inflation rate announcements.

As a proxy for volatility, realized volatility (RV) [5],, is used since it allows better short-term predictions by successfully modelling the clustering property of volatility [101]. Daily realized volatility is defined as follows:

$$RV_t(\Delta) = \left(\sum_{i=1}^{1/\Delta} r_{t,i}^2 \right)^{\frac{1}{2}}, \tag{25}$$

[5] Realized volatility is one of the most frequently used proxies for financial volatility [7, 11].

where $RV^2{}_t(\Delta)$ is the daily variance, Δ is interval length, $1/\Delta$ is an integer, $r_{t,i}$ is the intraday returns on day n. For instance, $1/\Delta = 76$ for the year 2015, with the 5-min returns.[6]

The RV statistics fulfills positive homogeneity property (positively homogeneous of degree 1):

$$H(\alpha R_t) = \alpha H(R_t) \text{ for } \alpha \geq 0, \tag{26}$$

$$H_t \equiv H(R_t) = H(\sigma_t \Psi_t) = \sigma_t H(\Psi_t), \tag{27}$$

where H is any positive and positively homogeneous proxy, H_t is the random variable and $H(\Psi_t)$ is independent of σ_t.

Within the scope of announcement effect analyses, intraday realized volatilities $r_{t,i}^2$ are used to compare against the forecasted volatilities.

As a proxy to measure the announcement effect, the ratio between the intraday realized volatilities and the corresponding intraday forecasted volatility is calculated. Using a one-sided t-test for each 5-minute interval, the null hypothesis of this ratio being significantly larger than 1 is tested. The t-test is one of the statistical tests used for hypothesis testing, such as Z-test, Chi-Square test and F-test for analysis of variance. The t-test is considered a more conservative approach than the Z-test and also better suited for smaller groups of data just as the case in this thesis:

H_0: Volatility Ratio is not higher than 1,

H_1: Volatility Ratio is higher than 1.

If the p-value of the t-test is smaller than 0.05, the realized volatility is significantly higher than the forecasted volatility.

---

[6] For the year 2015, the number of total 5-minute intervals is 76 with 36 coming from morning sessions between 09:35 and 12:30, and 40 coming from afternoon sessions between 14:15 and 17:30.

4.2.2.1. Announcement Effect Analyses for Interest Rate

The Central Bank of Turkey uses the Monetary Policy Committee (MPC) announcements as the main communication tool of the monetary policy. The MPC is made up of seven members and meets every month on pre-announced days. After the meeting, the MPC makes announcements of overnight (O/N) interest rates, one-week repo rate, and late liquidity window interest rates (between 16:00 – 17:00) with the brief reasons. The overnight interest rates are used as a policy rate by CBT in order to control the money supply in the economy, therefore the announcements of overnight interest rates are used for the event study analyses in this thesis.

The total realized change in interest rate (Δi), which is made by CBT on the announcement days, is divided into two main components: expected changes (Δi^e) and unexpected (surprise) changes (Δi^u):

$$\Delta i = \Delta i^e + \Delta i^u. \tag{28}$$

Since, only the unanticipated rate changes are assumed to have a significant effect on the financial markets [19, 30, 61, 74, 75, 85, 88, 91, 94], the unexpected component of the rate change can be measured by the changes in the rate of Treasury bonds traded on the announcement day with the shortest maturity [24, 70, 75]. The reason for using the government bond rate as a proxy reflecting policy expectations among marker participants is that government bonds with the shortest maturity (average of 30 days for the sample period) are the best financial instrument to reflect the effects of short-term events such as periodic economic announcements. In this context, the closing price of the government bond one day before the interest or inflation announcement is expected to reflect the expectations of the market participants regarding the next day's announcement. After the announcement at 14:00, the market is expected to adjust itself until the end of the day. If the market expectations for the interest rate changes are different than the actual rate changes made by CBT, the surprise component in Equation (31) is different from zero. Therefore, the unexpected rate change is calculated as the difference between the return of the government bond with the shortest maturity on the announcement day (Δi_t) and the return of the same bond one day before the announcement (Δi_{t-1}):

$$\Delta i^u = \Delta i_t - \Delta i_{t-1}. \tag{29}$$

Accordingly, the expected component (Δi^e) is equal to the remaining rate change:

$$\Delta i^e = \Delta i - \Delta i^u. \tag{30}$$

By making a comparison between the realized rate changes and the expected rate changes, interest rate announcements are classified into two groups in terms of whether the change is favorable or unfavorable. The classification criteria are explained in Table 6.

Table 6. Classification of Favorable and Unfavorable Interest Rate Announcements

Realized Rate	Expected Rate	Criterion	Result
Positive	Positive	$\lvert\Delta i\rvert < \lvert\Delta i^e\rvert$	Favorable
Positive	Positive	$\lvert\Delta i\rvert > \lvert\Delta i^e\rvert$	Unfavorable
Negative	Negative	$\lvert\Delta i\rvert > \lvert\Delta i^e\rvert$	Favorable
Negative	Negative	$\lvert\Delta i\rvert < \lvert\Delta i^e\rvert$	Unfavorable
Negative	Positive		Favorable
Positive	Negative		Unfavorable
No change	Positive		Favorable
No change	Negative		Unfavorable

4.2.2.2. Announcement Effect Analyses for Inflation Rate

In order to investigate the inflation rate announcement effects on the volatility of Borsa Istanbul, the realized inflation rate announced each month is compared with the target inflation rate announced at the beginning of each year[7]. If the realized rate is higher than the target rate, then it is inspected whether the realized rate is higher than the upper bound of the target rate band. During the sample period, each announced inflation rate is higher than the target rate, and in 33 out of 35 announcements, the rate is higher than the upper bound, all announcements are categorized as unfavorable surprises. Table 7 describes the classification of the inflation announcements as favorable versus unfavorable.

Table 7. Number of Favorable and Unfavorable Announcements

	Total # of	**# of Favorable**	**# of Unfavorable**
Inflation	35	0	35
Interest Rate	39	14	25

[7] The Central Bank of Turkey announces an inflation target at the beginning of each year and maintains that target for the next 12 months. The inflation target has a ±2 percent band around the middle rate.

CHAPTER 5

EMPIRICAL RESULTS AND DISCUSSION

In this chapter, first, the model estimation results are obtained. After the comparison between sGARCH and mcsGARCH models in terms of their powers of estimation and forecasting, the reasons for the selection of mcsGARCH model are explained in detail. Second, the results of the announcement effect analyses are explained in the event study section. The modelling, forecasting and plotting are conducted using R Programming.

5.1. Model Estimation Results

The mcsGARCH model has higher log likelihood value (see Table 10), which means that the mcsGARCH model's parameter estimations, with lower standard errors (see Table 8), have a higher probability of explaining the observed data. Also, mcsGARCH has lower mean absolute error (MAE) and root mean squared error (RMSE) terms, which means that the difference between the realized volatilities and the estimated volatilities obtained by the mcsGARCH model is smaller (see Table 10). As a result, the mcsGARCH model performs better than the sGARCH model according to the statistical parameters, as summarized in the Tables 8, 9, and 10.

Table 8. sGARCH vs. mcsGARCH - Parameter Estimation

Parameter	**Estimation**	**Std. Error**	**t-Value**	**p-Value**
		Standard GARCH(1,1)		
ω	0.0018	0.0001	20.1676	0.0000
α	0.1901	0.0075	25.4979	0.0000
β	0.7742	0.0067	115.1757	0.0000
		Multiplicative Component GARCH(1,1)		
ω	0.0071	0.0004	16.2397	0.0000
α	0.0404	0.0007	55.7872	0.0000
β	0.9533	0.0002	3874.0720	0.0000

Table 9. sGARCH vs. mcsGARCH - Information Criteria

Information Criteria	**sGARCH(1,1)**	**mcsGARCH(1,1)**
AIC	-1.4138	-1.5154
BIC	-1.4129	-1.5144
SIC	-1.4138	-1.5154
HQIC	-1.4135	-1.5151

Table 10. sGARCH vs. mcsGARCH – Evaluation Metrics

	sGARCH(1,1)	**mcsGARCH(1,1)**
Log Likelihood	49002.73	52526.56
MAE	0.0357	0.0298
RMSE	0.0042	0.0009

Figures 13 and 14 demonstrate the explanatory powers of the models sGARCH and mcsGARCH. The mcsGARCH model has a better estimation of conditional volatility against the real values.

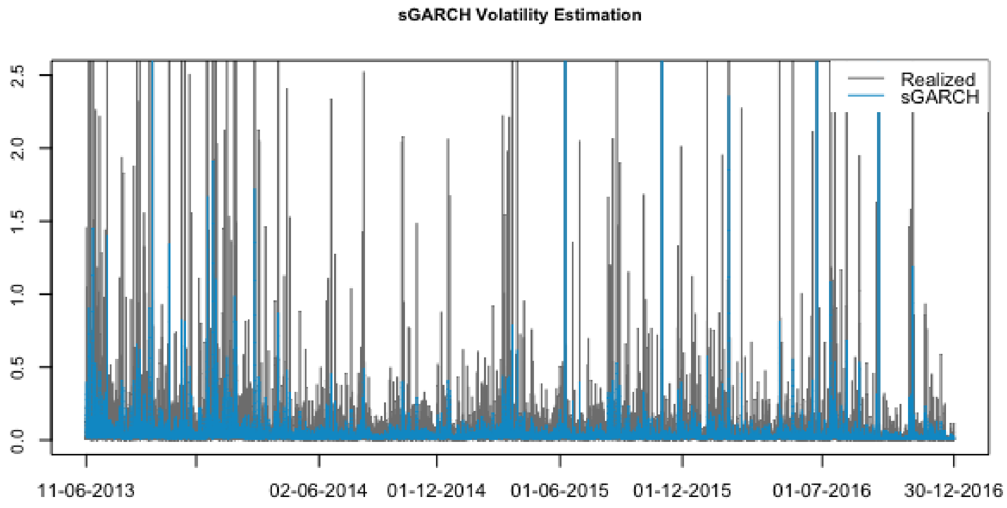


Figure 13. Conditional standard deviation vs realized standard deviation for the sGARCH model

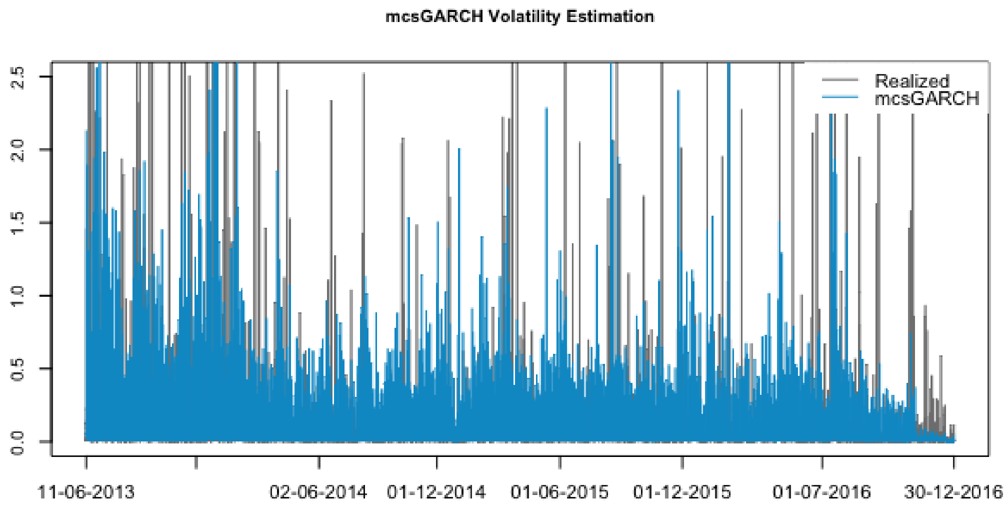


Figure 14. Conditional standard deviation vs realized standard deviation for the mcsGARCH model

If the model implemented is able to explain the serial correlation existing in the squared residuals, ACF of squared residuals should be similar to a discrete white noise process. Although both of the models could explain the serial correlation (Figures 15 and 16), from the density of standardized residual graphs (Figures 17 and 18), it is seen that mcsGARCH model can explain the intraday volatility better than sGARCH model.

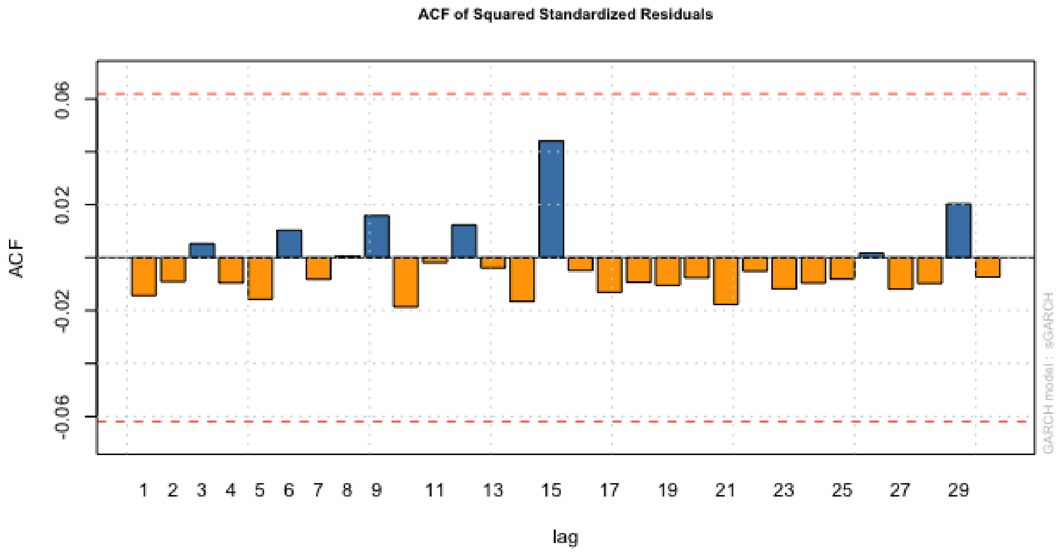


Figure 15. ACF of residuals from the sGARCH model

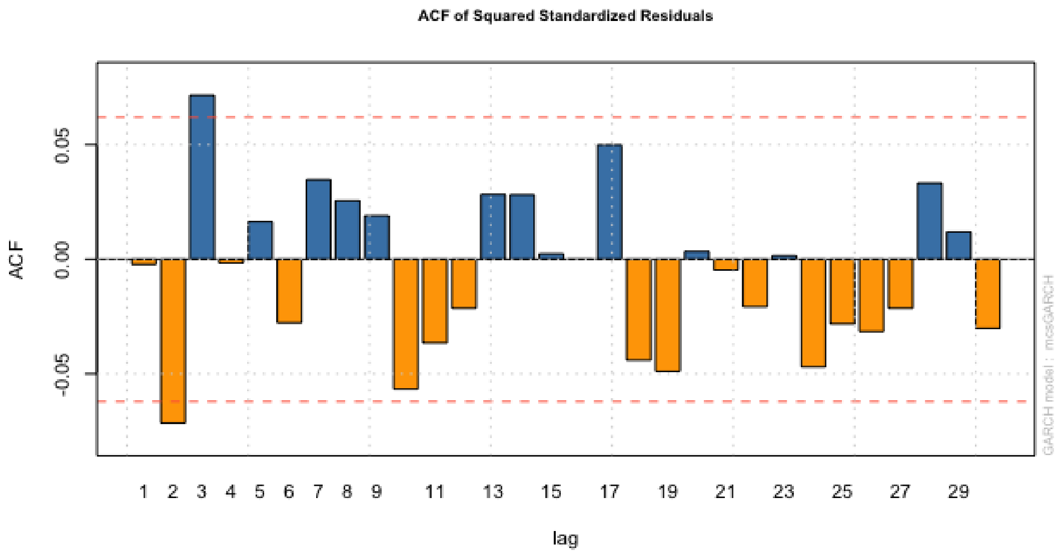


Figure 16. ACF of residuals from the mcsGARCH model

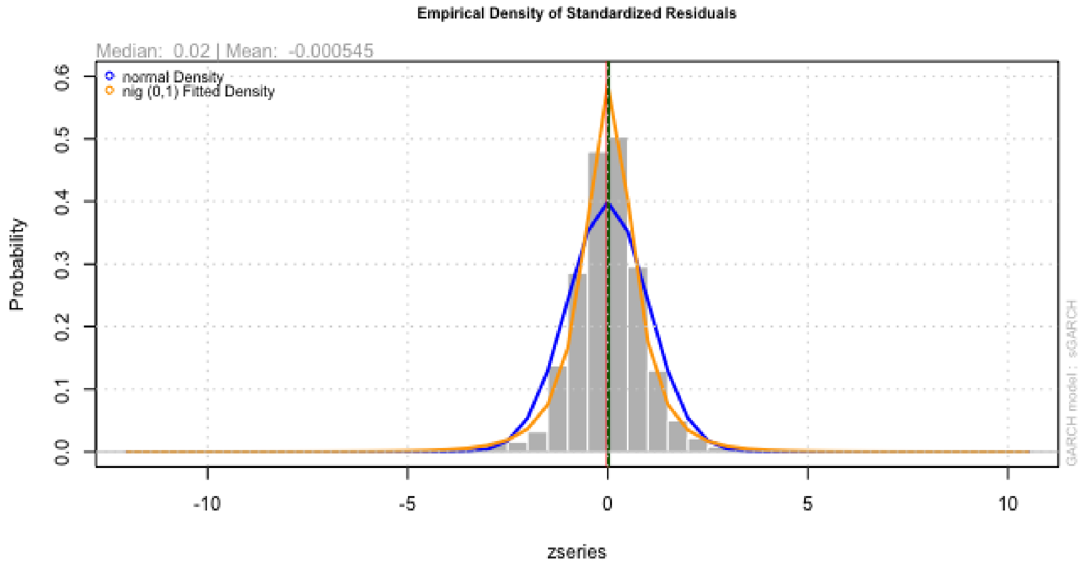


Figure 17. Residuals density - sGARCH

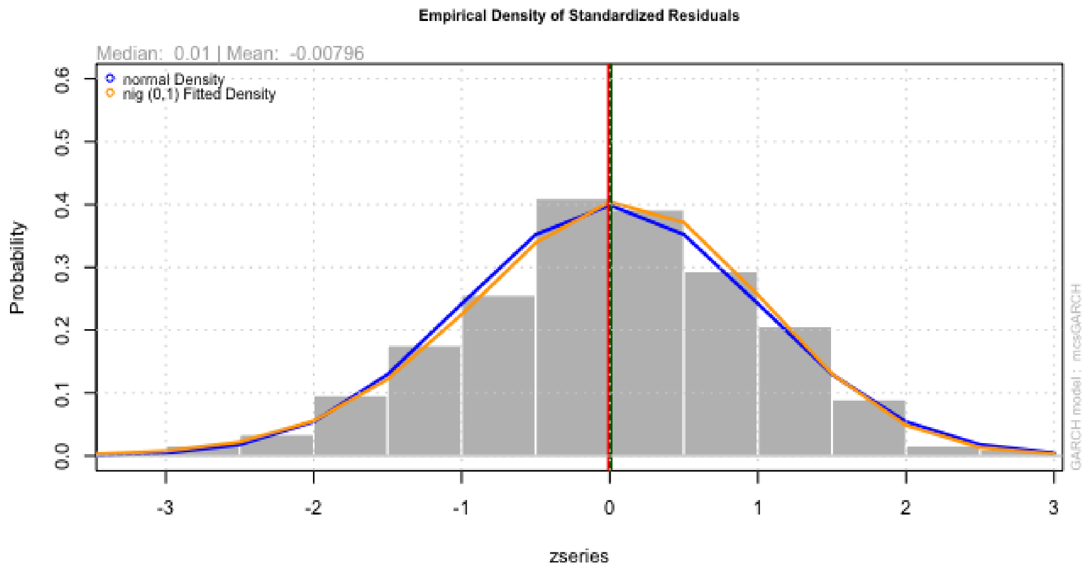


Figure 18. Residuals density - mcsGARCH

In addition to the fact that mcsGARCH provides a better fit to the 5-minute return data, it also performs better than the standard GARCH model in forecasting against the realized volatilities (see Figures 19 and 20). Unlike the standard GARCH model, the mcsGARCH model captures the diurnal pattern such as the high volatility observed at the market's open. Although the mcsGARCH somewhat overestimates the opening volatilities, it has still better intraday forecasting ability compared to the standard GARCH model.

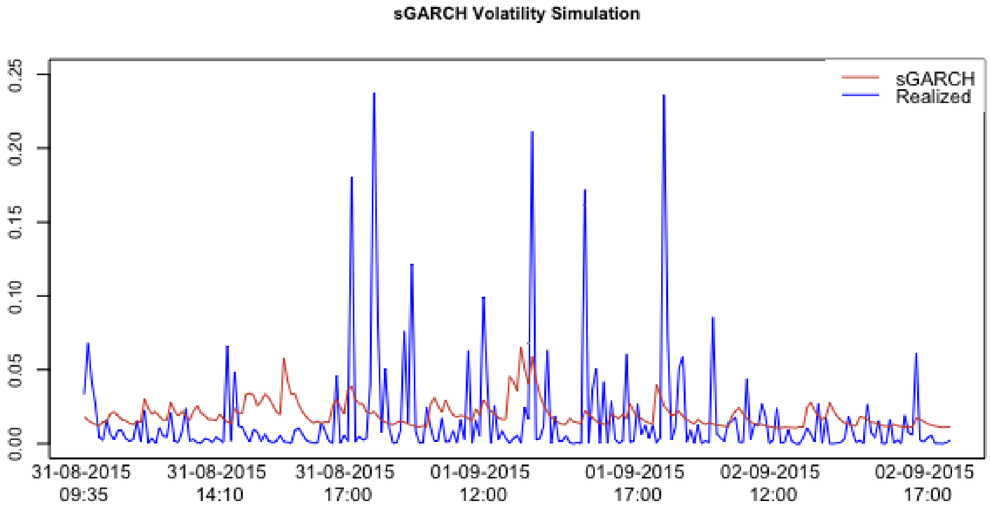


Figure 19. sGARCH volatility simulation

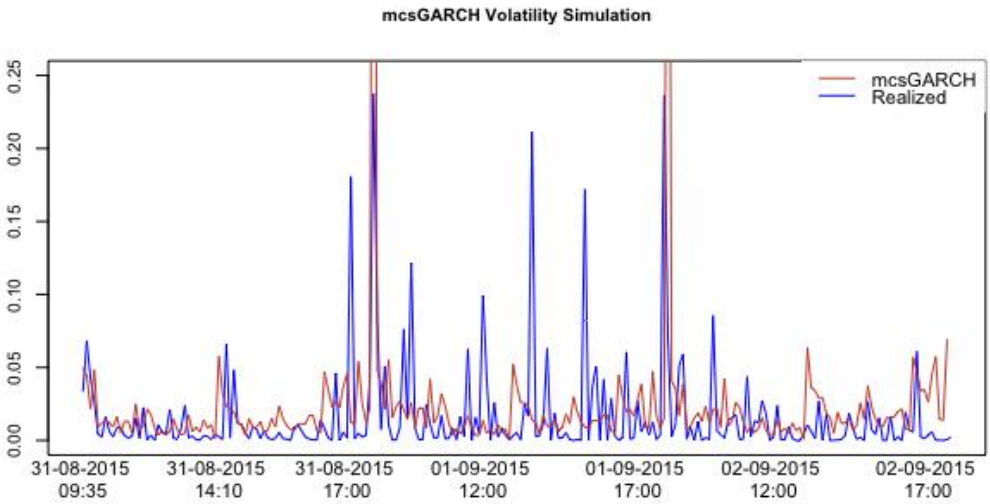


Figure 20. mcsGARCH volatility simulation

The standard GARCH model assumes that the volatility is fully stochastic and tries to explain this stochastic volatility with a variance model. On the other hand, the mcsGARCH model first divides the intraday volatility into three parts: diurnal, daily, and stochastic (see Figure 21). Next, it models the stochastic part of the volatility with the standard GARCH process. In other words, mcsGARCH is not completely different from sGARCH but it combines sGARCH and two other components (diurnal and daily). This section clarifies the reasons why the mcsGARCH model can capture the patterns of intraday return series better than the sGARCH model. In Figure 21, instead of the whole sample, randomly selected three-month data are used for the purpose of better illustration of the patterns.

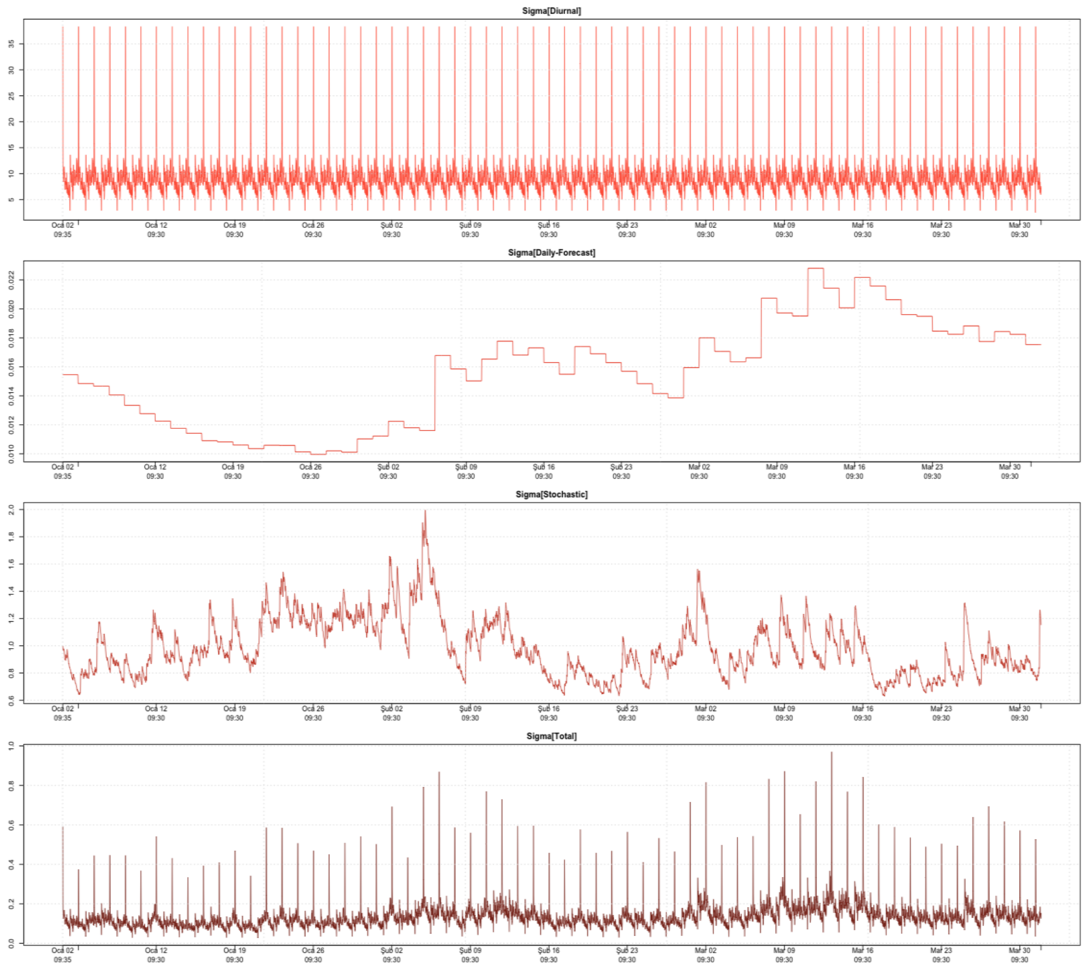


Figure 21. Diurnal, daily, stochastic, and total sigma estimation of the model

The first plot in Figure 21 shows the diurnal volatility component (s_i), the second one shows daily volatility component (h_t), the third one shows the stochastic volatility component ($q_{t,i}$), and the last one shows the total volatility. This figure indicates that the mcsGARCH model considers the patterns, which are the characteristics of intraday financial return series as explained in Chapter 3.

5.2. Event Study Results

After the selection of the mcsGARCH model for the 5-minute returns of BIST-30 Index, model estimations are done with the data of clear windows. Next, the intraday volatilities are forecasted for each corresponding event windows as explained in Figure 21. The comparisons between the realized and forecasted volatilities are done with the help of the t-test as explained in Chapter 4.

5.2.1. Interest Rate Announcement Effects

T-test results for the volatility ratios are given in Table 11. The results indicate that the BIST-30 Index starts responding to the interest rate announcements 15 minutes after the announcements at 14:00 and finishes reacting after 40 minutes.

Table 11. t-Test Results for Interest Rate Announcements

Time	**(Realized / Forecasted) Volatility Ratio**	**(Realized / Average) Volatility Ratio**
11:55	Difference is not significant	Difference is not significant
12:00	Difference is not significant	Difference is not significant
12:05	Difference is not significant	Difference is not significant
12:10	Difference is not significant	Difference is not significant
12:15	Difference is not significant	Difference is not significant
12:20	Difference is not significant	Difference is not significant
12:25	Difference is not significant	Difference is not significant
12:30	Difference is not significant	Difference is not significant
12:35	Difference is not significant	Difference is not significant
12:40	Difference is not significant	Difference is not significant
12:45	Difference is not significant	Difference is not significant
12:50	Difference is not significant	Difference is not significant
12:55	Difference is not significant	Difference is not significant
13:00	Difference is not significant	Difference is not significant
13:55	Difference is not significant	Difference is not significant
14:00	Difference is not significant	Difference is not significant
14:05	Difference is not significant	Difference is not significant
14:10	Difference is not significant	Difference is not significant

Table 11. (continued)

Time	**(Realized / Forecasted) Volatility Ratio**	**(Realized / Average) Volatility Ratio**
14:15	**Realized HIGHER than forecasted**	Difference is not significant
14:20	**Realized HIGHER than forecasted**	Difference is not significant
14:25	**Realized HIGHER than forecasted**	**Realized HIGHER than average**
14:30	**Realized HIGHER than forecasted**	Difference is not significant
14:35	**Realized HIGHER than forecasted**	Difference is not significant
14:40	**Realized HIGHER than forecasted**	Difference is not significant
14:45	Difference is not significant	Difference is not significant
14:50	Difference is not significant	Difference is not significant
14:55	Difference is not significant	Difference is not significant
15:00	**Realized HIGHER than forecasted**	**Realized HIGHER than average**
15:05	Difference is not significant	Difference is not significant
15:10	Difference is not significant	Difference is not significant
15:15	Difference is not significant	Difference is not significant
15:20	Difference is not significant	Difference is not significant
15:25	Difference is not significant	Difference is not significant
15:30	Difference is not significant	Difference is not significant
15:35	Difference is not significant	Difference is not significant
15:40	Difference is not significant	Difference is not significant
15:45	Difference is not significant	Difference is not significant
15:50	Difference is not significant	Difference is not significant
15:55	Difference is not significant	Difference is not significant
16:00	Difference is not significant	Difference is not significant

The t-test is repeated after the announcements are classified as favorable and unfavorable as described in Chapter 3. According to the results in Table 12, BIST-30 Index reacts to unfavorable interest rate announcements more and longer than favorable announcements during the sample period.

Table 12. t-Test Results for Favorable and Unfavorable Interest Rate Announcements

Time	**(Realized / Forecasted) Volatility Ratio**	**(Realized / Forecasted) Volatility Ratio**
	Favorable Surprises	*Unfavorable Surprises*
13:55	Difference is not significant	Difference is not significant
14:00	Difference is not significant	Difference is not significant
14:05	Difference is not significant	Difference is not significant
14:10	Difference is not significant	Difference is not significant

Table 12. (continued)

Time	(Realized / Forecasted) Volatility Ratio	(Realized / Forecasted) Volatility Ratio
	Favorable Surprises	*Unfavorable Surprises*
14:15	**Realized HIGHER than forecasted**	**Realized HIGHER than forecasted**
14:20	Difference is not significant	**Realized HIGHER than forecasted**
14:25	**Realized HIGHER than forecasted**	**Realized HIGHER than forecasted**
14:30	Difference is not significant	**Realized HIGHER than forecasted**
14:35	Difference is not significant	Difference is not significant
14:40	Difference is not significant	Difference is not significant
14:45	Difference is not significant	Difference is not significant
14:50	Difference is not significant	Difference is not significant
14:55	Difference is not significant	Difference is not significant
15:00	Difference is not significant	Difference is not significant
15:05	Difference is not significant	Difference is not significant
15:10	Difference is not significant	Difference is not significant
15:15	Difference is not significant	Difference is not significant

5.2.2. Inflation Rate Announcement Effects

The results of the t-tests for the volatility ratios are given in Table 13. The results indicate that the BIST-30 Index reacts to the inflation rate announcements only in the first 5 minutes immediately following the announcement at 10:00. Since May 2011, thus during the sample period, each announced inflation rate is higher than the target rate, and in 33 out of 35 announcements, the rate is higher than the upper bound. As a result, all announcements are categorized as unfavorable surprises. Thus, for the last years, market expectations are invariably that the inflation rate will be higher than the target rate, and it seems like the unfavorable announcements are no longer a surprise for the market participants. This may be the reason why the reaction is quite short-lived.

Table 13. t-Test Results for Inflation Rate Announcements

Time	(Realized / Forecasted) Volatility Ratio	(Realized / Average) Volatility Ratio
09:45	Difference is not significant	Difference is not significant
09:50	Difference is not significant	Difference is not significant
09:55	Difference is not significant	Difference is not significant

Table 13. (continued)

Time	**(Realized / Forecasted) Volatility Ratio**	**(Realized / Average) Volatility Ratio**
10:00	Difference is not significant	Difference is not significant
10:05	**Realized HIGHER than forecasted**	**Realized HIGHER than average**
10:10	Difference is not significant	Difference is not significant
10:15	Difference is not significant	Difference is not significant
10:20	Difference is not significant	Difference is not significant
10:25	Difference is not significant	Difference is not significant
10:30	Difference is not significant	Difference is not significant
10:35	Difference is not significant	Difference is not significant
10:40	Difference is not significant	Difference is not significant
10:45	Difference is not significant	Difference is not significant
10:50	Difference is not significant	Difference is not significant
10:55	Difference is not significant	Difference is not significant
11:00	Difference is not significant	Difference is not significant
11:05	Difference is not significant	Difference is not significant
11:10	Difference is not significant	Difference is not significant
11:15	Difference is not significant	Difference is not significant
11:20	Difference is not significant	Difference is not significant
11:25	Difference is not significant	Difference is not significant
11:30	Difference is not significant	Difference is not significant

CHAPTER 6

CONCLUSION

In this thesis, effects of interest rate and inflation rate announcements on the intraday volatility of the BIST-30 Index are analyzed by using the multiplicative component GARCH model with 5-minute data. The contribution of this thesis can be described from two aspects. First, multiplicative component GARCH model was not used for announcement effect analyses in the literature. Since, multiplicative component GARCH model offered by Engle and Sokalska [41] is relatively a new model, the applications are limited with two empirical studies. Diao and Tong [32] applied this model to 5-minute returns of CSI 300 Index and shows that mcsGARCH model performs well in Chinese stock market. Nachnani [80] compares GARCH(1,1) and mcsGARCH models with the application to 1-minute, 5-minute, 10-minute and 15-minute return series. The findings indicate that although the mcsGARCH model provides good results for most of these frequencies, it performs better at higher frequencies such as 1-minute and 5-minute intervals. These findings coincide with this thesis as explained in Chapter 5. Second, periodic macroeconomic announcements used after the adoption of the inflation targeting regime in Turkey were not analyzed with intraday data and either with the standard GARCH or the mcsGARCH models.

When the lower frequency data are used for the analyses of announcement effects on the stock market, endogeneity and omitted-variable bias problems may hinder the estimation process. The advantages of using high-frequency data for the announcement effect analyses are (i) the ability to see the intraday reactions, and (ii) the opportunity to explain short-run volatility changes immediately after the announcement event with a much smaller probability of confounding events driving the results.

The results for the interest rate announcements indicate that the market starts to react within 15 minutes of the announcements and the reaction continues until after 40 minutes for the whole sample. After separating the type of the announcements as favorable and unfavorable, the reaction times are observed to change. According to the results, unfavorable interest rate announcements have a longer impact on the stock market volatility as compared to favorable announcements (20 minutes versus 5 minutes, respectively).

For the inflation rate case, the results indicate that inflation rate announcements increase the BIST-30 volatility in the first 5 minutes immediately following the announcement. In addition, the market reaction to inflation announcements seems to be faster compared to that of interest rate announcements. However, the effect is much shorter and it disappears after the first 5 minutes. The inflation rate target could not be met since 2011, and the market seems to have adapted to the discrepancy between the target and actual inflation rates.

The limitations of the study should be expressed clearly. Since the sample period is relatively short and does not include all the years since the adaptation of the inflation targeting regime, the changes in the announcement effects over the years, cannot be observed. Therefore, the effects of switching to the inflation targeting regime cannot be analyzed.

As future analyses, volume data can be included to the volatility and/or return model. Also, the modeling and forecasting can be applied to the different sector indices, which have different financial dynamics, to see the effects of interest rate and inflation rate shocks. Returns can be modeled by allowing asymmetric reactions to the direction and magnitude of the announcement surprises. The last suggestion is to investigate the effects of foreign economic announcements, such as FED and ECB announcements, on the local stock market.

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APPENDICES

Appendix A. ANNOUNCEMENT DAYS

Interest Rate Announcement Days	Inflation Rate Announcement Days
23.07.2013	03.07.2013*
20.08.2013	05.08.2013
17.09.2013	03.09.2013
23.10.2013	03.10.2013
19.11.2013	04.11.2013
17.12.2013	03.12.2013
21.01.2014	03.01.2014
28.01.2014*	--
18.02.2014	03.02.2014*
18.03.2014	03.03.2014
24.04.2014	03.04.2014
22.05.2014	05.05.2014
24.06.2014	03.06.2014
17.07.2014	03.07.2014
27.08.2014	04.08.2014
25.09.2014	03.09.2014
23.10.2014	03.10.2014
20.11.2014	03.11.2014
24.12.2014	03.12.2014
20.01.2015	05.01.2015
24.02.2015	03.02.2015
17.03.2015	03.03.2015
22.04.2015	03.04.2015
20.05.2015	04.05.2015
23.06.2015	03.06.2015
23.07.2015	03.07.2015
18.08.2015	03.08.2015
22.09.2015	03.09.2015
21.10.2015	05.10.2015
24.11.2015	03.11.2015
22.12.2015*	03.12.2015*
19.01.2016	04.01.2016
23.02.2016*	03.02.2016*
24.03.2016	03.03.2016*

Appendix A. (continued)

Interest Rate Announcement Days	**Inflation Rate Announcement Days**
20.04.2016	04.04.2016*
24.05.2016	03.05.2016
21.06.2016	03.06.2016
19.07.2016	04.07.2016
23.08.2016	03.08.2016
22.09.2016	05.09.2016
20.10.2016	03.10.2016
24.11.2016*	03.11.2016
20.12.2016	05.12.2016*

*Announcements excluded from the analyses

Appendix B. TEZ FOTOKOPİSİ İZİN FORMU

ENSTİTÜ

Fen Bilimleri Enstitüsü	
Sosyal Bilimler Enstitüsü	
Uygulamalı Matematik Enstitüsü	X
Enformatik Enstitüsü	
Deniz Bilimleri Enstitüsü	

YAZARIN

Soyadı : YILMAZ
Adı : Berna Nisa
Bölümü : Finansal Matematik

TEZİN ADI (İngilizce) : Macroeconomic Announcements and Intraday Stock Market Volatility

TEZİN TÜRÜ : Yüksek Lisans [X] Doktora [ ]

1. Tezimin tamamından kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
2. Tezimin içindekiler sayfası, özet, indeks sayfalarından ve/veya bir bölümünden kaynak gösterilmek şartıyla fotokopi alınabilir. [ ]
3. Tezimden bir bir (1) yıl süreyle fotokopi alınamaz. [X]

TEZİN KÜTÜPHANEYE TESLİM TARİHİ: