INTRADAY PRICE REVERSALS WITH HIGH FREQUENCY DATA: APPLIED TO BIST 100 INDEX

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF APPLIED MATHEMATICS
OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

FATİH CİNGÖZ

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
FINANCIAL MATHEMATICS

FEBRUARY 2021

Approval of the thesis:

INTRADAY PRICE REVERSALS WITH HIGH FREQUENCY DATA: APPLIED TO BIST 100 INDEX

submitted by **FATİH CİNGÖZ** in partial fulfillment of the requirements for the degree of **Master of Science in Financial Mathematics Department, Middle East Technical University** by,

Prof. Dr. A. Sevtap Selçuk-Kestel _____
Director, Graduate School of **Applied Mathematics**

Prof. Dr. A. Sevtap Selçuk-Kestel _____
Head of Department, **Financial Mathematics**

Assoc. Prof. Dr. Adil Oran _____
Supervisor, **Business Administration, METU**

Examining Committee Members:

Prof. Dr. A. Sevtap Selçuk-Kestel
Actuarial Sciences, IAM, METU _____

Assoc. Prof. Dr. Adil Oran
Business Administration Department, METU _____

Assist. Prof. Dr. Başak Tanyeri
Faculty of Business Administration, Bilkent University _____

Date: _____

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name: FATİH CİNGÖZ

Signature :

ABSTRACT

INTRADAY PRICE REVERSALS WITH HIGH FREQUENCY DATA: APPLIED TO BIST 100 INDEX

Cingöz, Fatih

M.S., Department of Financial Mathematics

Supervisor : Assoc. Prof. Dr. Adil Oran

February 2021, 68 pages

Investors are willing to exploit opportunities to earn abnormal profits. Event study methodology has received considerable attention to catch these opportunities. However, the literature dealing with short-term reactions to large price movements is quite small regarding emerging markets because of difficulties in collecting intraday dataset. In this thesis, we contribute to the literature by providing evidence about the existence of overreaction and intraday reversal effect over a 13-year period from an emerging market. The Istanbul Stock Exchange National 100 Index XU100 (BIST 100) is chosen for the analyses. The event set includes the days that experience price changes exceeding a prespecified threshold at the market open, and hypotheses of the results are tested using various statistical tests. The results document that overreaction in the market lasts only for a few minutes, and reversal happens after the second minute of the trading day. Additionally, our long-term investigation shows evidence in favor of major magnitudes of reversal as threshold levels rise, consistent with the previous findings in reversal literature.

Keywords: Overreaction, Reversal, Intraday

ÖZ

YÜKSEK FREKANSLI VERİLERLE GÜN İÇİ FİYAT GERİ DÖNÜŞÜM HAREKETLERİ: BIST 100 ENDEKSİ ÜZERİNE BİR UYGULAMA

Cingöz, Fatih
Yüksek Lisans, Finansal Matematik Bölümü
Tez Yöneticisi : Doç. Dr. Adil Oran

Şubat 2021, 68 sayfa

Yatırımcılar piyasalarda oluşacak fırsatları yakalamak ve bunlardan anormal getiri elde etmek isterler. Olay analizi, bu fırsatları ortaya çıkarmak, piyasaların etkinliği ve anomalileri gibi konuları değerlendirmek için başvurulan yöntemler arasındadır. Literatüre bakıldığında, gelişen piyasalarda yüksek frekanslı veri setlerine ulaşmanın kolay olmamasından dolayı büyük fiyat hareketlerine piyasaların verdiği kısa dönemli tepkiler üzerine çalışmalara pek rastlanmamaktadır. Bu tezde, gün içi aşırı tepki ve geri dönüş anomalisi, 13 yıllık periyot üzerinden Borsa İstanbul BIST 100 endeksi üzerinde test edilmiştir. Gecelik getirileri belli bir seviyeyi aşan günler vaka kümesine dahil edilmiştir. Bulgular çeşitli istatistiksel metotlar kullanılarak test edilmiştir. Çalışmanın sonucunda, vaka kümesine dahil olan günlerde aşırı tepkinin açılıştan itibaren bir dakika sürdüğü ve geri dönüş hareketlerinin bu dakikadan sonra başladığı gözlemlenmiştir. Buna ek olarak, kullanılan filtre seviyesi arttıkça daha güçlü geri dönüş hareketlerinin yaşandığı bulunmuştur. Bu durum, daha önceki çalışmalarda sergilenen sonuçlarla tutarlılık göstermektedir.

Anahtar Kelimeler: Aşırı Tepki, Geri Dönüş, Gün İçi

To My Family

ACKNOWLEDGMENTS

Firstly, I would like to express my gratitude to my thesis advisor Assoc. Prof. Dr. Adil Oran for his kindness, enthusiastic encouragement, and valuable advice he provided in the development and preparation of this thesis. I feel lucky for studying on a topic that really attracts me and gives me considerable pleasure. Therefore, I would like to thank my advisor for his guidance to find that subject.

I would like to thank Berna Nisa Yılmaz for encouraging me to learn programming in R and I would like to express my very great appreciation to my colleague Dr. Mustafa Nal for his endless support and contribution.

Finally, I would like to thank Prof. Dr. Selcuk Kendirli and my colleagues in my office for their patience and the limitless tolerance they showed through the process of researching and writing this thesis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BIST	Borsa Istanbul
UK	United Kingdom
US	United States
IMKB	Istanbul Menkul Kıymetler Borsası
ACR	Average Cumulative Return
CR	Cumulative Return

CHAPTER 1

INTRODUCTION

Efficient Market Hypothesis, which was formulated by Fama [27], says that prices reflect all available information at any point of time and follow a random walk pattern meaning that predictions on future prices are not applicable. With the notion of an efficient market, investors can not beat the market consistently by doing research or planned investment strategy without bearing more risk than the market. However, rapid and continuously releasing information in markets may make it tough to sustain efficiency and may lead to deviations from market patterns' expected behavior. In the academic finance community, these deviations are called market anomalies that refer to situations when prices are not based on rational evaluation and when price patterns seem to violate the efficient market hypothesis.

Market anomalies have attracted many researchers and investors and motivated them to test the reliability of market efficiencies. According to the results of many studies, some anomalies emerged and died away over time, while others can be observed in markets even today. Researchers have found some anomalies, and they are commonly classified as fundamental, technical, and calender based anomalies. Many researchers have used event studies as a tool to detect these anomalies and poke holes in the theory of efficient markets.

In behavioral finance literature, some studies have been conducted for assessing the role of sentiments in asset pricing beyond the role of fundamentals [21, 8, 5, 7]. Furthermore, Some studies, Shiller [63] and Akerlof and Shiller [1] have tried to explain the presence of anomalies by irrational behaviors like herding, instant panic. The other irrational behavior of investors is that investors tend to evaluate recent informa-

tion improperly. In light of all these irrational behaviors, new anomalies have come out in the course of time. The overreaction phenomenon is one branch of them. Although the representative idea that traders use former performance to appraise future value was suggested by Kahneman and Tversky [38], the first evidence of the overreaction hypothesis was provided by a famous paper of DeBondt and Thaler [21] titled "Does the Market Overreact?". They basically proposed that if prices revert to the initial level after an extreme movement, it is evidence of overreaction bias meaning the market has overreacted to available relevant information. By contrast, a continuation in the former price pattern documents the existence of underreaction bias. They also proposed a basic strategy under the overreaction hypothesis, a contrarian strategy. A contrarian investor expects those past losers will rebound and past winners will sag as the market perception is adjusted in a latter session (Venter [68]).

The tendency of explaining these reversals by overreaction has attracted many researchers, and event studies related to overreaction have become ubiquitous in behavioral finance literature (Numan and Andonov [56]). The literature dealing with the overreaction hypothesis is mainly based on US stock markets but have been studied in other countries also [44, 3, 43, 50, 52]. Moreover, some researchers have also studied it in different security markets [58, 47, 34, 62].

The great majority of the overreaction literature concentrate on long term price reactions. Although short-term analysis of price reactions is significant, the literature dealing with this case is quite limited regarding emerging markets because of difficulties in gathering the required intraday dataset. The papers that used intraday datasets usually investigate the shape of volatility and return patterns. The presence of higher volatility in opening and closing trading sessions was found by most of these studies. Some of them have linked the causes of this volatility pattern experienced in the openings to the accumulation of information and uncertainty, which is induced by market closure [32, 45, 28, 25]. Additionally, Lin et al. [49] point out that significant herding behavior is larger in the opening interval. Similar results have also been documented by some empirical studies related to Borsa Istanbul (BIST) and its predecessor the Istanbul Stock Exchange (IMKB) as [12, 36, 33, 37]. These papers have also provided that volatility of return dynamics is not symmetric at the opening and closing sessions. Furthermore, Ekinci [26] point out that trading activity mostly occurs to a

greater extend in openings and just before closings.

The previous studies' common findings illustrate clear evidence that volatility and intraday return patterns tend to be different at the beginning of the day and the end of the trading day. In accordance with these arguments, the intraday overreaction phenomenon defined by subsequent price reversals following large price changes at the market open has not been handled as other anomalies in the literature. There is limited evidence in stock markets related with intraday reversal effect [29, 40, 34, 30, 22, 59, 70, 66]. The empirical results of these studies have documented the existence of short-term overreaction and subsequent price correction.

Besides the confirmation of the short-term overreaction hypothesis regarding the U.S. and other markets, to the best of our knowledge, there is not any conducted research that examines intraday overreactions by using the high-frequent Borsa Istanbul dataset. The existing intraday studies related to Borsa Istanbul have focused exclusively on the volatility of return pattern. Thus, it is important to exhibit results with other datasets from an emerging market to check the robustness of this temporary market anomaly. Therefore, we have analyzed the intraday market trend following extreme price movements at market openings. The aim of this thesis is twofold. Firstly, it attempts to identify the existence of short-term overreaction and reversal effects. Secondly, it examines the magnitude of these effects. The Istanbul Stock Exchange National 100 Index XU100 (BIST 100) is chosen for the analyses. The sample period runs from February 2, 2007[1] to February 2, 2020. Hypotheses of the results are tested using various statistical tests (parametric and non-parametric tests).

We find a significant overreaction and intraday reversal effect over a 13-year period in case of extreme overnight gaps. Consistent with the previous findings in reversal literature [34, 29, 40, 64], we also document statistically significant intraday price reversals mainly at the opening of the market. The results illustrate that overreaction in the market lasts only for a few minutes following large price changes at the market open. Reversals happen after the second minute of the trading day, and the index value converts back to its initial level in ten minutes. Additionally, our long-term investigation shows evidence in favor of major magnitudes of reversal as filter levels

[1] It is the day that call auction system was introduced, where the orders are matched at the equilibrium price.

rise.

To the best of our knowledge, this thesis is the first study investigating on short-term overreaction phenomenon for Borsa Istanbul; thus, it contributes to the existing literature on the short-term overreaction hypothesis. Moreover, by conducting filter based methodology and studying the longest to date high-frequency data, we enhance the vast literature on event studies in Turkey.

CHAPTER 2

LITERATURE REVIEW

Proponents of the efficient market hypothesis assume that prices would reflect almost all available information. However, behavioral finance considers that investors are not always rational, and under or overreaction to the information is possible. In the sense of overreaction, prices would increase far from their fair values, then followed by price movements in the reverse direction. Therefore, investors can exploit this information and create a portfolio with a contrarian strategy, which is basically taking a long position in past losers and taking a short position in past winners. De Bondt and Thaler [21] examined this strategy in their celebrated study. They constructed portfolios based on contrarian strategy and compared their performance to a benchmark market index. They documented that the portfolio, which consists of past losers, consistently beat the market index. On the other hand, the portfolio consists of past winners consistently underperformed against the benchmark index. After this celebrated study, subsequent contributions to the profitability of contrarian strategies were reported by papers such as [61, 15, 16]. Following these studies, Baytas and Cakici [10] showed evidence of the profitability of contrarian strategies on different markets other than U.S. markets. They tested the strategy on G-7 countries while Gaunt [31] tested it for the Australian market. Both of the two studies contribute to the previous findings. On the other hand, Kryzanowski and Zhang [44] found that the strategy did not work in Canadian Markets. They tested the strategy using monthly data and showed that there is no significant reversal in Canadian stocks.

Usually, the early papers examined it over long holding periods. Following studies reported that contrarian strategy also works for shorter holding periods. Mun

et al. [54] structured short-term contrarian portfolios based on German and French stocks. The performance of their portfolios indicated an overreaction phenomenon in the short-term. One year later, Mun et al. [55] conducted an analysis covering U.S. and Canadian stock markets. Their short and intermediate-term contrarian portfolios were profitable for the U.S. market. In stark contrast to the findings of Kryzanowski and Zhang [44], they also exhibited excess return for Canadian stocks with their intermediate-term portfolios. Kang et al. [39] investigated 260 stocks belong to China stock market by a weekly dataset. Short-term contrarian strategies were found to be profitable. McInish et al. [51] examined the reliability of contrarian strategy in several markets such as Singapore, Thailand, Malaysia, Hong Kong, Korea, Japan, and Taiwan. They set short-term contrarian and momentum strategies considering various factors. Apart from the Korean and Taiwan markets, they illustrated that overreaction bias holds for winner portfolios in all markets. Miralles et al. [52] documented that overreaction to the positive shocks is stronger in a bear market. They conducted this study in the Spanish stock market. Lalwani et al [46] examined the overreaction anomaly in ten stock markets from different countries. They analyzed average cumulative abnormal returns over six days following price shocks and demonstrated existing of overreaction in eight markets. They further stated that investors perceive positive and negative news differently.

Thanks to the availability of high-frequency data, the number of studies regarding the overreaction effect on an intraday basis has been increasing. Generally, the intraday overreaction hypothesis has been determined as existing of price reversals following extreme price movements at the open. Although long-term overreaction studies generally examined the hypothesis on a portfolio basis, some of the short-term studies have focused on the stock market index or index futures. For example, [30, 34, 29] have examined short-term overreaction phenomenon on the basis of index values. Grant et al. [34] investigated short-term reversal following large price movements at the open. They found strong evidence of short-term overreaction over 15 years for S&P 500 index futures. Moreover, they stated that reversals are more powerful after large positive price changes. Fung et al. [30] conducted relatively a shorter-term study comparing to the one of Grant et al. [34]. They examined the hypothesis on the S&P 500 Futures market and the HSI Futures market. They reported a larger magnitude of

price reversals due to the greater price changes at the open. Both of the studies used predefined thresholds as filters to specify the event set, which consists of the days experiencing price movements beyond the filters. Fung et al. [30] used relatively lower filters than the one used by Grant et al. [34] to have more observations. The existence of price reversal was also found by the study of Fung et al. [29]. They used a different technique to define the event set. They calculated pricing errors based on the gap between the previous day's closing futures price and the closing index value of the Hong Kong market. Miwa and Ueda [53] tried to provide evidence of intraday price reversals on two Japanese stock index futures contracts. Also, they examined the impact of the extension of trading hours on it. They found significantly intraday price overreaction and reported that the magnitude of overreaction is positively correlated with extended trading hours. Tripathi and Aggarwal [66] contributed to the literature by examining the hypothesis in a different market. Using high-frequency intraday data in the Indian stock market, they reported price reversals to occur within a few minutes following large price movements. Stübinger and Schneider [64] applied an alternative way, the jump test model, to detect overnight gaps. Their dataset covered S&P 500 stocks from January 1998–December 2015. They documented that overreaction occurs during the first minutes of a trading day. In addition to these studies, Zhang et al. [71] tried to explain intraday price reversals based on investor types. They discovered that price reversals happen mainly by retail investors' attitudes in Chinese and U.S. stock markets. While most of the studies mentioned above have applied a fixed threshold level to identify event days, some of them used standard deviations as a tool to define threshold levels [46, 50].

Researchers have also studied the short-term overreaction hypothesis on other security markets. Poteshman [62] investigated price patterns of the options market following extreme price changes. He reported that investors underreact to instant changes. Cooper et al. [18] tested the short-term contrarian strategy in the real estate market. They documented that as the filter level increases, the more profitable the strategy becomes. Larson and Madura [47] examined the hypothesis among currencies of developed and emerging countries. Their findings suggested that the overreaction effect is more powerful for emerging countries. A similar study was made by Parikakis and Syriopoulos [58]. Two developed and two emerging countries, respectively, the

US, UK, Turkey, and Brazil, were selected to be tested with regard to exchange rate movements of their currencies. They reported overreaction in the Turkish lira, the Brazilian real, and the US dollar. The British pound, on the other hand, exhibited an underreaction effect. Caporale and Plastun [14] analyzed price gaps using daily data in various markets such as stock, FOREX, and commodity markets. They observed anomaly only in the FOREX market.

A large number of existing studies have been reported that short-term overreaction holds following extreme price movements. However, some papers taking into account transaction costs for simulation of contrarian strategies showed that investors could not profit from these strategies. For example, Atkins and Dyl [4] did not deny the evidence of overreaction in NYSE listed stocks. Nevertheless, once bid-ask spreads are considered, the contrarian strategy becomes no more profitable. Contributing to the findings of Atkins and Dyl [4], Kaul and Nimelandran [42], Cox and Peterson [20] and Conrad et al. [17] have also supported that advantage of the strategy disappears when the bid-ask spread is considered. Contrary to these findings, Lehmann [48] showed that it is possible to gain profit from price reversals despite transaction costs. Fung et al. [30] also found supportive results for profitable reversal strategies after considering bid-ask spreads. A later study by Venter [68] provided reliable results concerning bid-ask spread bias. Examining contrarian strategy over the Johannesburg Stock Exchange, reversal effects were presented under the assumption of mid-quote pricing. However, when he changed the assumption as best bid-ask pricing, the reversal effect was largely eliminated. Some studies have tested the overreaction hypothesis regarding capitalization (Antoniou et al. [3], Maher and Parikh [50]). These studies were conducted for the UK equity market and the Indian stock market, respectively. They found similar results that small and mid-cap indices experience underreaction.

The long-term based overreaction hypothesis is valid in the Turkish stock market according to some studies [69, 13, 6, 24, 2]. Yücel and Taşkın [69] created contrarian portfolios over 1-year, 2-year, and 3-years formations. Their datasets span from 1992 to 2005. According to their findings, the overreaction hypothesis holds for all of the portfolios with various lengths of formation, and the magnitude effect is stronger for winner portfolios. Bildik and Gülay [13] tested the profitability of various contrar-

ian strategies. They consider not only historical returns but also size, book-to-market ratio, and price. The results supported overreaction in the Turkish stock market for different holding periods spanning from 1 month to 36 months. Barak [6] examined the price dynamics of stocks over 5 years periods. It is founded that past loser/winner stocks become winner/loser in the next 5 years horizon. Doğukanlı et al. [24] conducted contrarian strategies with various time horizons. They reported the presence of reversals for most of the winner and loser portfolio formation. Alper and Aydoğan [2] tested the profitability of contrarian strategies with formation over a period of one to five years. They tracked the performance of portfolios for the following periods of one to five years. All of the portfolios they constructed demonstrated that overreaction is valid in Borsa Istanbul. In stark contrast to these findings, Dizdarlar and Reyhan [23] stated that there is no overreaction anomaly in Borsa Istanbul. They examined contrarian portfolios' performance in different test periods, such as January to December, June to May, and August to July. Testing the strategy over a period of one year, they could not find any evidence for overreaction anomaly in the Turkish stock market.

The literature dealing with the short-term overreaction phenomenon based on the Turkish stock market is limited. Using the daily closing value of the BIST 100 index, one of them was conducted by Tetik ve Ozen [65]. They investigated how the market index reacts to the positive and negative events formed in the Dow Jones industrial index. They found that abnormal returns of the BIST 100 index significantly increased after 60th days following positive events in the Dow Jones industrial index. However, no significant result was found following negative events. Karan and Tarım [41] tested the overreaction hypothesis on the stocks listed in the Turkish stock market. Their event set included stocks affected by limit up and down restrictions. They divided the study into two pieces. Overreaction on the stocks that reach price limit of 10% was investigated before June 12th, 1994[1] and the stocks that reach price limit of 20% was selected to be tested after June 12th, 1994[2]. They found evidence of overreaction on the stocks that experienced falling prices in both periods. They also found overreaction for the winner stocks in the second period. However, no overreaction effect was found for the winner stocks in the first period. Daiyrbek [67] chose

[1] Covering the days, when Turkish stock market held a single session.
[2] Two session era began at Turkish stock market.

his thesis topic similar to the former study conducted by Karan and Tarım [41], but he tested the overreaction effect with a totally different dataset. Stocks that reached the predefined threshold, which refers to various daily price limits, were included in the event set. Overreaction was reported for the stocks that following positive price changes. Contrary to the findings of Karan and Tarım [41], no reversal movements were detected on the negative side. Furthermore, it is stated that overreaction takes place in a shorter time period comparing to the findings of previous studies. While Karan and Tarim [41] determined that the market reacts after 5 trading day following price movements, Daiyrbek [67] found that the overreaction effect begins on the second or third trading day. Polat et al. [60] considered the Borsa Istanbul sports index to check whether overreaction exists in this specific market. The limit for extreme price movements was defined as two standard deviations in their study. Overreaction was examined following the days that exceed this limit. According to the results, a reversal effect was not found on the sports index.

As an intraday study and using similar methodology to our research, Oncu et al. [57] tried to detect overreaction on an hourly basis. The dataset covered the days from October 10, 2001 to May 26, 2006. The authors analyzed 20 stocks listed in the Dow Jones Turkey Titans 20 Index and calculated market-adjusted overnight returns of them. As a result of the analysis, a sample of 80 observations, which is relatively small to our sample size, was revealed. Their findings showed that market participants overreact in the first hour, and then price reversals start.

CHAPTER 3

DATA & METHODOLOGY

3.1 Samples

The BIST 100 index is chosen to test the intraday overreaction hypothesis in the Turkish stock market. The index comprises the largest and most widely traded 100 stocks listed on the Borsa Istanbul from various sectors. Kang et al. [39] reported that small firms tend to incorporate new common information into their prices slowly. Thus, the BIST 100 index, which represents the market's general attitude, is most convenient to see the presence of overreaction. The high-frequency data regarding BIST 100 index is supplied from Borsa İstanbul Historical and Reference Data Platform. The data stores the index price for every 10 seconds before November 30, 2015 and for every second after that date[1]. The sample period runs from February 2, 2007[2] to February 2, 2020, a thirteen-year study.

Turkish stock market held two separate sessions for the equity market and had a midday trading break. However, midday break has been no longer applied in the Borsa Istanbul as of October 4, 2019. Currently, the market opens at 10:00 am and closes at 6:00 pm. There is a pre-market session from 9:40 am to the market opening. For the first 15 minutes during the pre-market session, investors can confirm or modify their orders. Between 9:55 am to 10:00 am, the orders are matched, and the opening price is determined. A similar process holds for the closing call auction sessions, which was introduced on March 2, 2012. Therefore, each trading day's opening and closing

[1] Following the introduction of BISTECH, BIST 30 and BIST 100 price indices start being calculated and disseminated every second during the trading session.

[2] The first day of call auction system during the opening session.

Table 3.1: Trading Hours Changes in the Equity Market of Borsa Istanbul

Dates	Trading_Session_Hours
From 1 January 1986 to 13 August 2001	10:00 to 12:00 and 14:00 to 16:00
From 13 August 2001 to 7 February 2007	9:30 to 12:00 and 14:00 to 16:30
From 2 February 2007 to 7 September 2007	10:00 to 12:00 and 14:00 to 16:30
From 7 September 2007 to 13 October 2008	9:45 to 12:00 and 14:00 to 17:00
From 13 October 2008 to 19 October 2009	9:50 to 12:30and 14:00 to 17:00
From 19 October 2009 to 13 November 2009	9:50 to 12:30 and 14:00 to 17:30
From 13 November 2009 to 5 March 2012	9:50 to 12:30 and 14:30 to 17:30
From 5 March 2012 to 16 July 2012	9:50 to 12:30 and 14:15 to 17:15
From 16 July 2012 to 5 April 2013	9:50 to 12:30 and 14:15 to 17:30
From 5 April 2013 to 11 June 2013	9:45 to 12:30 and 14:15 to 17:30
From 12 June 2013 to 30 November 2015	9:35 to 12:30 and 14:15 to 17:30
From 30 November 2015 to 14 November 2016	9:35 to 12:30 and 13:30 to 17:30
From 14 November 2016 to 4 October 2019	10:00 to 13:00 and 14:00 to 18:00
From 4 october 2019 to current	10:00 – 18:00

prices are determined as settlement prices as of March 2, 2012. Before that date, we use the last transaction price to identify the closing price. Hours of opening and closing sessions have been modified several times over the years. Table 3.1 provides the details regarding these changes. As seen in the Table 3.1, the duration of trading halts has also been changed many times. Therefore, it would not be reliable to estimate cumulative returns after a trading halt due to the unequal accumulation of information. On the other hand, Borsa Istanbul has recently employed a single trading session without any trading halt. Thus, studying price gaps separately for each session would not be beneficial to investors. Furthermore, most Turkish stock market studies have provided clear evidence about trading activity, volatility, and intraday price pattern [37, 12, 36, 33, 26]. According to the common findings, higher trading volume and volatility mostly occur at the beginning and the end of the trading day. In light of these facts, we include the first 120 minutes and the last 60 minutes of each trading day to the sample.

The dataset contains some missing values. The days with missing values are excluded from the analysis. Since we need the opening price and the prior day's close price for each trading day, excluded days are checked to see whether they have an impact on the research[3]. Then we transform the transaction data into minute-by-minute intervals. Closing prices are taken into account for each minute. As we survey the sample on an ordinal basis, the first 120 minutes and the last 60 minutes of each trading day,

[3] Please see the Table D.1 in Appendix D.

the results of the study are not effected by changes in trading hours. Thanks to the long-term data, we expect to observe different market conditions, such as bullish or bearish. Thus, we assume that the study is free of selection bias.

3.2 Methodology

3.2.1 Methodology for the short-term overreaction hypothesis in BIST

The thesis aims to identify short-term overreaction and intraday price reversals in the BIST 100 index. Event study methodology based on the approaches of Fung et al. [30] and Grant et al. [34] is used to facilitate this analysis. Following the technique on these papers, overnight price gaps should be detected first, and then the event set should be defined as when the overnight gaps exceed a prespecified filter level.

The identification of overnight gaps is done by the help of following formula:

$$OR_i = {}^{P_{i,open}}/_{P_{i-1,close}} - 1 \tag{3.1}$$

where overnight gap is denoted by the OR on day i; $P_{i,open}$ presents the open price on day i; $P_{i-1,close}$ represents the close price on day $i-1$.

Once the overnight price gaps are determined, the fixed threshold strategy or the simple filter-rule methodology [30, 34, 14, 18] is applied to define event days using the following criteria:

$$EventDays = \begin{cases} OR_i \geq f_1, & f_1 \in \{0.005, 0.01, 0.015\} \\ OR_i \leq f_2, & f_2 \in \{-0.015, -0.01, -0.005\} \end{cases} \tag{3.2}$$

$$NormalDays = \{OR_i = f_3, \quad -0.005 < f_3 < 0.005$$

where OR_i denotes the overnight gap on day i; f_1, f_2 and f_3 represent the given filter sizes.

Days that meet the condition given in equation 3.2 are classified as an event day. To explain more clearly, if the overnight gap for any day i is equal to or larger than the given range of filter sizes f_1, the day i is included in the event set. Similarly, day i is classified as an event day whenever the overnight gap at day i is equal to

Table 3.2: Number of Gaps for Different Filter Sizes

	Filter Sizes (%)*											
	$\geq$ $+0.25$	$\geq$ $+0.5$	$\geq$ $+1$	$\geq$ $+1.5$	$\geq$ $+2$	$\leq$ -0.25	$\leq$ -0.5	$\leq$ -1	$\leq$ -1.5	$\leq$ -2	$<$ $\|0.25\|$	$<$ $\|0.5\|$
#obs[1]	1372	749	267	117	27	703	460	211	121	40	1135	2001
%obs[2]	42.7	23.3	8.3	3.6	0.8	21.9	14.3	6.6	3.8	1.2	35.3	62.3

Note: #obs in the study of Grant et al (2005): 980 positive gap, 864 negative gap.

[1] number of observations; [2] percentage of observations.

* Total population in our study is 3210.

or smaller than given filter sizes f_2. Normal days include any day i experiencing an overnight gap smaller than the absolute value of 0.5%. The level of filter sizes covered in this analysis is larger than the one used by other studies (Fung et al. [30] and Grant et al. [34]). Considering the lower stock market liquidity and volatility pattern in emerging markets (İnci and Özenbaş [37]), we set up threshold points as 0.5%, 1%, 1.5% for both positive and negative side to carry out a sufficient number of observations and to examine the magnitude effect. As seen in the Table 3.2, a larger filter level than the absolute value of 1.5% is not considered because of the relatively smaller sample sizes, which would weaken the reliability of statistical results. We define the normal days as experiencing a morning gap smaller than the absolute value of 0.5%, considering the percentage of the population they represent. As a different approach from other similar studies, we try to look at whether there is a significant difference between event days and normal days.

After determining the set of event days and normal days, the cumulative returns at the predefined minutes are calculated for each trading day by:

$$CR_{i,t} = {}^{P_{i,t}}/_{P_{i,0}} - 1 \tag{3.3}$$

where $t \in \{1, ..., 10, 15, 20, 25, 30, 45, 60, 75, 90, 105, 120, last60, last30, last15, close\}$ [4]; $P_{i,t}$ presents the price of index at minute t after opening on day i; $P_{i,0}$ represents the opening price on day i; $CR_{i,t}$ denotes the cumulative return of the index at minute t on day i.

[4] We consider the last trading interval (15, 30 and 60 minutes) before the closing due to the shifting of trading hours. Last60, last30 and last15 represent the gap 60,30 and 15 minutes before closing, respectively. Close determines the closing price.

Note that Grant et al. [34] studied intraday reversals with 5 minutes intervals, which may lead to miss out possible earlier overreaction movements. Therefore, we also concentrate on the first minutes of the trading day to identify short-term overreaction patterns in a more detailed way. Before conducting the statistical tests, average cumulative return for each minute t is calculated by the formula below:

$$ACR_t = \frac{1}{N}\sum_{i=1}^{N} CR_{i,t} \tag{3.4}$$

where N represents the total number of days corresponding to a given filter for each event set. Note that ACR_t is calculated for event days and normal days separately.

Finally, we check the significance of results by conducting various tests. Based on the studies regarding intraday reversals [30, 34, 52, 64], we follow a similar approach to compare the results and perform a t-test as;

$$t_t^s = (ACR_t^s - 0) \Big/ \left(\sigma_{CR_t^s} \Big/ \sqrt{N}\right) \tag{3.5}$$

where s defines the event days; ACR_t^s represents average cumulative return at minute t on event days; $\sigma_{CR_t^s}$ denotes the standard deviation of the cumulative returns at minute t for event days and N is the number of observations with related to given filter size. The test is applied to each minute t and each filter size.

The t-test is employed to see whether the mean of returns for minute t is significantly different from zero. Therefore, we test the null hypothesis that the sample mean is equal to zero for each minute t. However, Corrado [19] said that parametric tests could provide imprecise inferences in case of non-normality of data[5]. Motivated by the concern of non-normality, we consider applying both parametric and non-parametric tests that do not depend on an assumption of normally distributed[6]. As a non-parametric alternative to the one-sample t-test, we employ the one-sample Wilcoxon Signed-Rank Test to check the null hypothesis that the median of ACR_t^s is equal to zero[7].

[5] To check the distribution of return series for each minute, we conduct Shapiro test and Ansari-Bradley test regarding normality and variance equality, respectively. We observe that returns have non-normal distribution and unequal variance in most of the cases. Test results are provided in the Appendix B for ease of presentation.

[6] Based on the review of 75 event studies relevant with Turkey, Basdas and Oran [9] reported that parametric tests are preferred mostly. They stated that parametric and non-parametric tests should be used together due to high non-normality in returns.

[7] Please see Appendix C for the test procedure.

We move forward with different statistical tests for robustness checks. Two sample statistical tests are carried out to compare return patterns of event days and non-event days. Welch's t-test, reliable with unequal variance, is applied to see the significance of the difference in means between the two groups. The following equation is used to obtain the t statistic:

$$t_t = \frac{ACR_t^s - ACR_t^n}{\sqrt{\frac{\sigma^2_{CR_t^s}}{N_s} + \frac{\sigma^2_{CR_t^n}}{N_n}}} \tag{3.6}$$

where ACR_t^s and ACR_t^n represent average cumulative return of each minute t for event days and non-event days, respectively; $\sigma_{CR_t^s}$ and $\sigma_{CR_t^n}$ denote the standart deviation of the cumulative returns at minute t for event days and normal days; N_s presents the sample size of event days and N_n presents the sample size of non-event days. The null (H_o) and alternative (H_1) hypothesis of the two-sided Welch's T-test are expressed as:

$$H_0 : ACR_t^s = ACR_t^n.$$
$$H_1 : ACR_t^s \neq ACR_t^n.$$

The Mann Whitney U test, as an alternative non-parametric test which does not require equal variances or sample size, is also applied to examine whether a significant difference of medians between event days and normal period (non-event days) exists[8]. The test is conducted for each minute t. The null (H_o) and alternative (H_1) hypothesis of the test are as follow:

H_0: The median for the two groups are equal.

H_1: The median for the two groups are not equal.

The empirical results of these analyses are presented in Section 4.1. Note that a two-tailed hypothesis is performed, and confidence levels of 95% are considered for each test employed. All calculation routines are completed with the help of R programming.

3.2.2 Second part of the short-term overreaction hypothesis

In the previous section, the filter sizes of 0.5%, 1%, and 1.5% are used to test the overreaction phenomenon. However, one may question whether the smaller filter

[8] Test formula is provided in Appendix C.

size results are affected by relatively larger initial price gaps. Therefore, we consider the process of decomposition filter sizes. In this section, by providing evidence on different sub-filters, we test the consistency of the magnitude effect in the short-term overreaction hypothesis.

We follow the same procedure that is applied in Section 3.2.1. For the sake of simplicity, equations are not exhibited here again. Firstly, overnight gaps are found from equation 3.1. Then, we adopt the following method to define event days[9] :

$$
\begin{aligned}
EventDays = \begin{cases} OR_i = f_1, & 0.5\% \leq f_1 < 1\% \\ OR_i = f_2, & 1\% \leq f_2 < 1.5\% \\ OR_i = f_3, & -1\% < f_3 \leq -0.5\% \\ OR_i = f_4, & -1.5\% < f_4 \leq -1\% \end{cases} \\
NormalDays = \{OR_i = f_5, \quad -0.5\% < f_5 < 0.5\%
\end{aligned}
\tag{3.7}
$$

where OR_i denotes the overnight gap on day i; f_1, f_2, f_3, f_4 and f_5 represent the given filter sizes.

To see the magnitude effect clearly, one of the events set consists of the days whose OR is equal to or larger than 0.005 and smaller than 0.01. The days with an opening gap between 0.01 and 0.015 are included in the event set to be examined separately. The days with negative overnight gaps corresponding to the filter size of -0.005 to -0.01 and -0.01 to -0.015 are also investigated. The days whose overnight gap smaller than the absolute value of 0.005 represent the normal days.

For the available event and normal days, cumulative return and average cumulative return for each minute t are calculated from equation 3.3 and 3.4. T-test and One-Sample Wilcoxon Signed-Rank Test are applied to each minute t and each event set. Then, Welch's t-test and Mann-Whitney U test are employed to compare the mean and median of returns between the event and normal sets. Note that, in this part, we test the same null and alternative hypothesis similar to the one used in Section 3.2.1 for all corresponding tests with confidence levels of 95%. The findings are reported in Section 4.2.

[9] Since we have the results for absolute filter size 1.5% in the previous section, they are omitted here.

CHAPTER 4

RESULTS

4.1 First Part of Overreaction Hypothesis

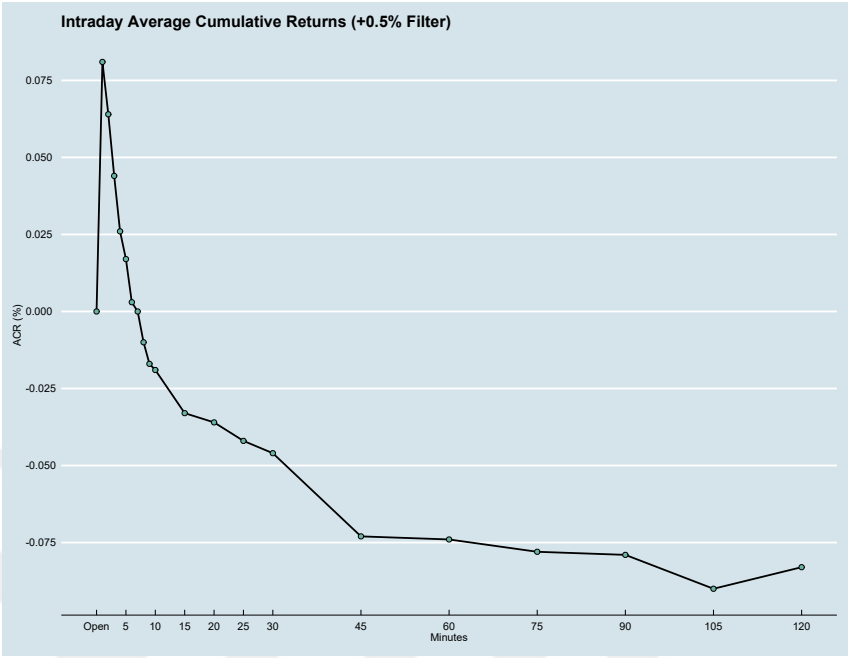
4.1.1 Overreaction Following Positive Overnight Gaps

In this part, we provide the findings of reversals configurations following positive overnight gaps. ACRs of corresponding minute t are shown in Table 4.1,4.2 and 4.3 regarding three different filter sizes used as a threshold in this study. Relying on the graphical images in Figure 4.1a,4.2a and 4.3a, existence of overreaction and price reversals following positive overnight gaps are clearly seen for all given filter sizes. The overreaction effect occurs heavily in the first minutes following openings. Market participants then adjust their behavior throughout the trading day.

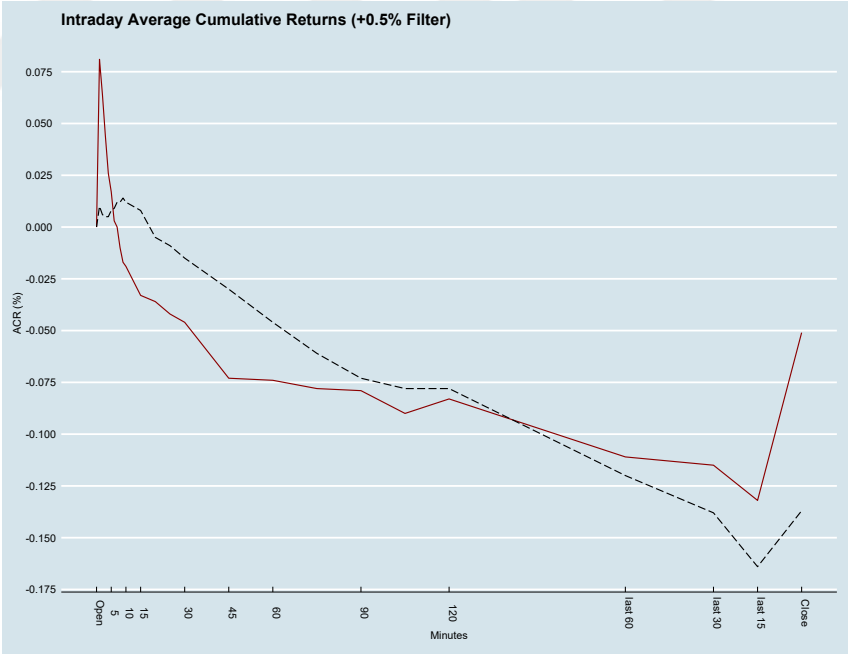
For the lowest filter, 0.5%, the index surges in the first minute and reaches a peak of 0.081%. After that, it experiences a reversal and back to its initial position in 7 minutes. Price reversals last beyond the 15 minutes before closing. However, the strongest part of reversals occurs in the first 45 minutes, falling to -0.073%. Index reaches its minimum of -0.132% in the last 15 minutes of trading days. Relying on Figure 4.1b, deviations are clearly higher in the first 10 minutes between the event and normal days. After 10 minutes, both event sets show similar return patterns. Statistical results show the significant difference in the first four minutes. Looking at the p-values of Welch's t-test in the Table 4.1, we mostly reject the null hypothesis that ACRs of event and non-event days are equal in the first 60 minutes. Also, the hypothesis of having the same distribution or median for both event sets is mostly

rejected in corresponding duration as seen in the results of the Mann-Whitney U test. However, the test results confirm that the impact of extreme price changes on return pattern is not obvious after an hour following opening. T-test results indicate that ACRs are significantly different from zero at a 5% level for 17 out of 24 conditions. We can not reject the null hypothesis for the second 5 minutes interval. Moreover, the t-test and Wilcoxon test results allow us to report that the mean and median of cumulative returns for event days are not significantly different from zero at closing.

Looking at the Figure 4.2a, it is seen that the overreaction phenomenon also holds for the 1% filter. Appreciation of index lasts only one minute, and investors correct their sentiments later. Both overreaction and reversals occur in a stronger way comparing to the 0.5% filter level. Index return rises to 0.108% in the first minute and reverses to 0.088% in the second minute. Positive yield maintains in the first five minutes. Then index converges to its opening level and experiences a sharp decrease until the first 45 minutes. It keeps on falling but gradually toward to last 15 minutes closing interval. Figure 4.2b shows that, after five minutes, the line of returns for event days is far below than normal days. Also, note that it marks the minimum of -0.226%, which is relatively lower than that in the case of 0.5% filter. Statistical tests imply highly significant results for the 1% filter. Equality of mean and median between two event sets is mostly rejected for the first 105 minutes of trading days. Furthermore, one sample parametric and non-parametric tests provide similar significant results. We mostly reject the null hypothesis.



(a) Return Pattern of Event days for the first two hours



(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.1: Daily Return Patterns Following Positive Overnight Gaps (0.5% Filter)

Table 4.1: ACR and Test Results of Event Days After Opening ($|0.5\%|$ Filter)

Minutes	Filter: +0.5%					Filter: -0.5%				
		p-values					p-values			
		One Sample		Two Sample			One Sample		Two Sample	
	ACR(%)	T	W	W's	U	ACR(%)	T	W	W's	U
1	0.081	0 *	0 *	0 *	0 *	-0.068	0 *	0 *	0 *	0 *
2	0.064	0 *	0 *	0 *	0 *	-0.064	0 *	0 *	0 *	0 *
3	0.044	0 *	0 *	0 *	0 *	-0.036	0.027 †	0.004 *	0 *	0.016 †
4	0.026	0.012 †	0 *	0.006 *	0.065 ‡	-0.015	0.41	0.227	0 *	0.296
5	0.017	0.13	0.002 *	0.06 ‡	0.463	0.011	0.569	0.501	0 *	0.868
6	0.003	0.797	0.049 †	0.144	0.652	0.034	0.093 ‡	0.031 †	0 *	0.235
7	0	0.982	0.169	0.056 ‡	0.373	0.061	0.005 *	0 *	0 *	0.03 †
8	-0.01	0.457	0.568	0.048 †	0.125	0.069	0.002 *	0 *	0 *	0.016 †
9	-0.017	0.211	0.911	0.018 †	0.041 †	0.091	0 *	0 *	0 *	0.001 *
10	-0.019	0.171	0.993	0.004 *	0.042 †	0.101	0 *	0 *	0 *	0 *
15	-0.033	0.028 †	0.362	0.005 *	0.014 †	0.13	0 *	0 *	0 *	0 *
20	-0.036	0.027 †	0.524	0.03 †	0.09 ‡	0.141	0 *	0 *	0 *	0 *
25	-0.042	0.012 †	0.377	0.024 †	0.073 ‡	0.128	0 *	0 *	0 *	0 *
30	-0.046	0.008 *	0.21	0.024 †	0.116	0.123	0 *	0 *	0 *	0 *
45	-0.073	0 *	0.025 †	0.081 ‡	0.047 †	0.164	0 *	0 *	0 *	0 *
60	-0.074	0 *	0.028 †	0.253	0.238	0.135	0 *	0 *	0 *	0 *
75	-0.078	0 *	0.032 †	0.384	0.503	0.12	0 *	0 *	0 *	0 *
90	-0.079	0.001 *	0.049 †	0.245	0.828	0.114	0.001 *	0 *	0 *	0 *
105	-0.09	0 *	0.016 †	0.232	0.673	0.11	0.003 *	0 *	0 *	0 *
120	-0.083	0.002 *	0.073 ‡	0.215	0.871	0.111	0.005 *	0 *	0 *	0 *
last60	-0.111	0.015 †	0.162	0.102	0.849	0.014	0.844	0.291	0 *	0.068 ‡
last30	-0.115	0.019 †	0.183	0.059 ‡	0.677	0.054	0.455	0.106	0 *	0.013 †
last15	-0.132	0.01 *	0.161	0.036 †	0.572	0.029	0.702	0.216	0 *	0.016 †
Close	-0.051	0.338	0.804	0.003 *	0.155	0.17	0.033 †	0.005 *	0 *	0 *

Note: ACR : Average Cumulative Return; T : T-test; W : Wilcoxon Test; W's : Welch's T-test; U : Mann Whitney U Test

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level

When we look at the Figure 4.3a and Table 4.3, the conclusion display consistent patterns with former filter levels but the magnitude of reversals is stronger for 1.5% filter. Increasing with a brief period following an initial price change, market participants seem to be more aggressive when adjusting the value of information, which leads to the dropping of returns at a great pace. ACR converges to zero in four minutes after opening. From the Figure 4.3a, we see that continuation of sharp decrease is powerful for the first 10 minutes where the return of -0.167 is marked. ACR declines smoothly throughout the day and reaches its minimum of -0.425% at the 15 minutes before closing. Statistical test results are very similar to those for filter 1%, and report highly significant results for overreaction and reversal effect. According to Welch's t-test, we reject the null hypothesis for all cases at a 10% level.

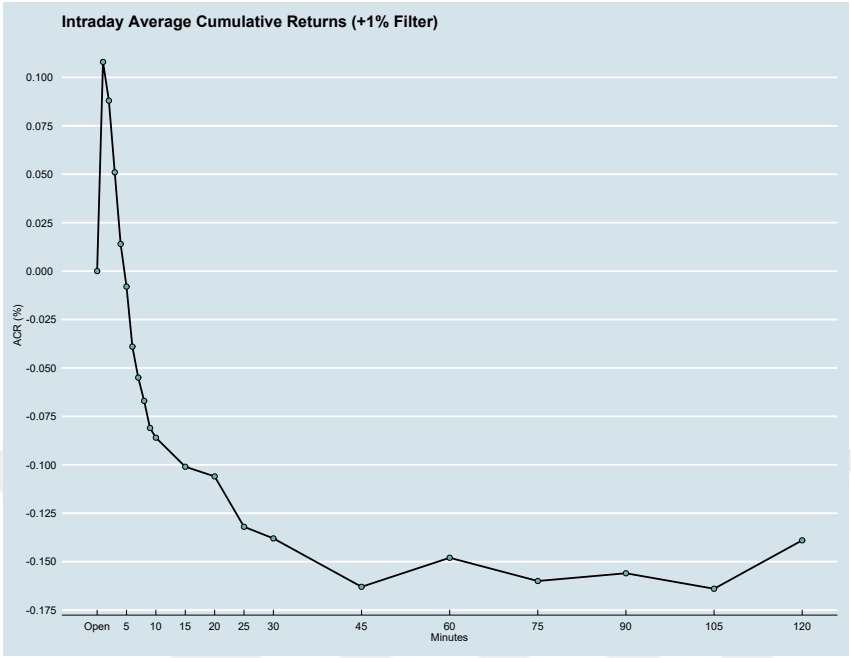
The analysis shows that significant intraday reversals exist in the morning following positive extreme overnight gaps on the BIST 100. Given the range of filters, a reaction for correction starts in the second minute after opening. Therefore, intraday overreaction in BIST lasts a shorter time comparing to that found in other studies [34, 68, 64] in different markets. We also observe that converging to the opening level takes less time and the magnitude of reversal becomes larger as the filter level increases.

4.1.2 Overreaction Following Negative Overnight Gaps

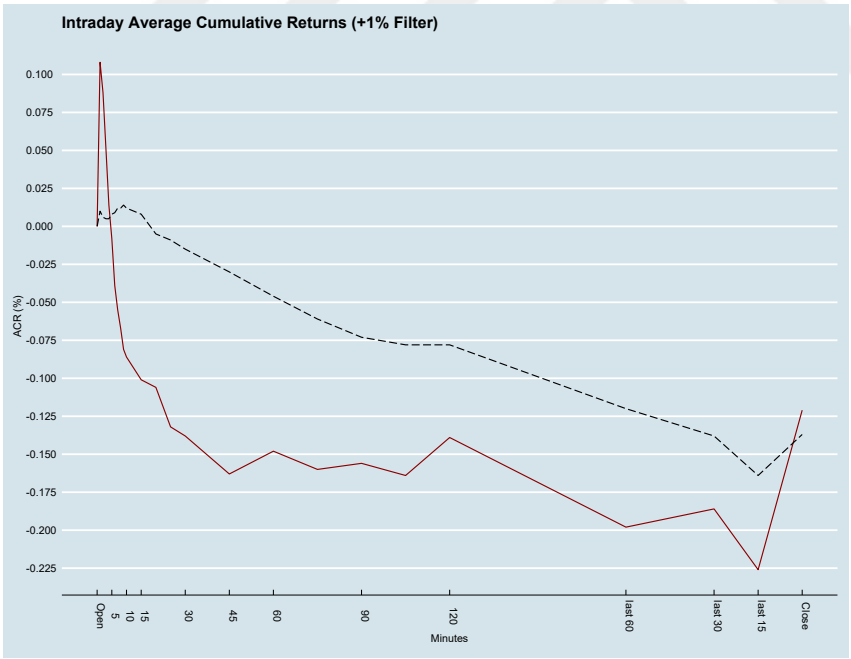
We also analyze the short-term overreaction and reversal phenomenon in case of extreme negative overnight gaps. Three filter sizes are used as a threshold to determine event days. Regarding the same absolute filter sizes, we observe a lower number of samples on the negative side[1]. The results confirm the existence of overreaction but more weakly than that on the positive side.

Considering -0.5% filter, overreaction exists only in the first minute after opening. ACR reaches the -0.068% in that minute, which is relatively smaller than the initial reaction following a positive corresponding gap. Then correction begins; however, the market continues to yield negative return until the 5^{th} minute. Converging to the initial level takes less time than the positive side, which takes place in 7 minutes. Looking at the Figures 4.4a and 4.4b, it is clear that ACR pattern exhibits a differ-

[1] Please see the tables in Appendix A.

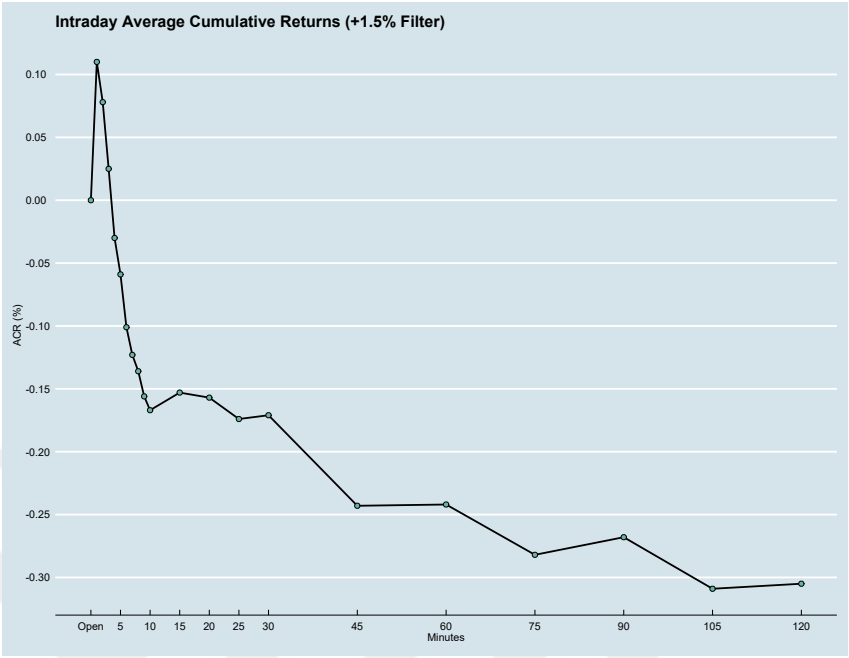


(a) Return Pattern of Event days for the first two hours

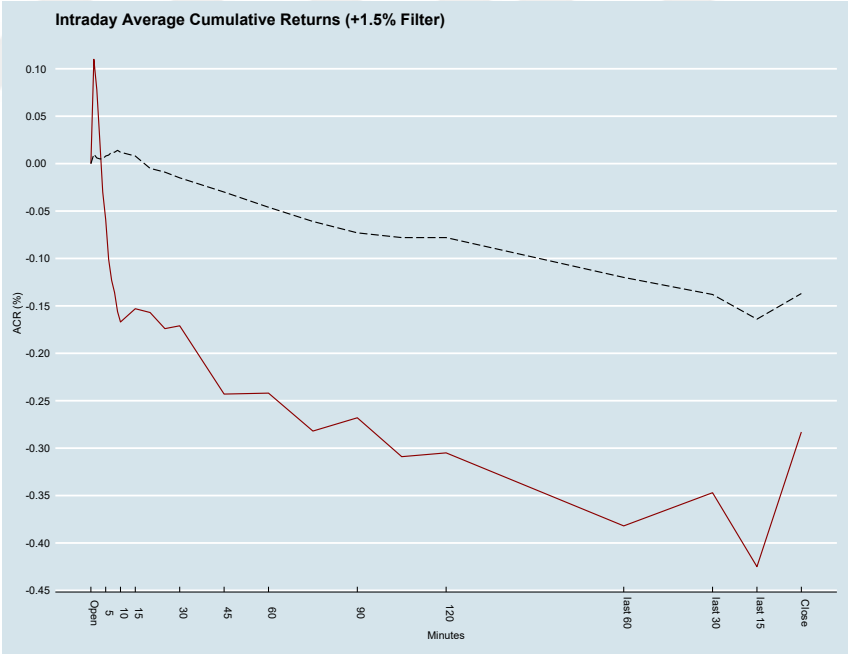


(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.2: Daily Return Patterns Following Positive Overnight Gaps (1% Filter)



(a) Return Pattern of Event days for the first two hours



(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.3: Daily Return Patterns Following Positive Overnight Gaps (1.5% Filter)

ent view compared to the Figures 4.1a and 4.1b. Market return reverses to its high, 0.164%, in 45 minutes but not on a straight line. Then it keeps falling to 0.0295% until the last 15 minutes of the trading day. At the end of the day, it rises to its maximum of 0.170%. In the case of a positive gap, when the reversal starts, market return displays a steady drop. On the other hand, it carries potential volatility throughout the day following negative overnight gaps. Comparing the statistical test results, we obtain more significant p-values in the case of negative gaps than positive gaps. Results of Welch's t-test provided in Table 4.1 allow us to confirm that ACRs for the event and normal days are not the same in any minute at 1% significance level. Other test results, as seen in Table 4.1 also report that we can reject the null hypothesis in most of the cases.

We find consistent results with -1% filter regarding the overreaction hypothesis. The general finding says that market participants overreact to the available information just for one minute following opening. Falling to -0.092% in 1 minute, ACR reverses and has a yield of -0.018% in 4 minutes. Then it crosses the zero line and rebounds to 0.266% in 45 minutes. Experiencing some deviations, ACR declines to 0.070% at the last one hour. Its peak performance of 0.308% comes at closing. Highly significant test results are found with Welch's t-test. P-values obtained from the Mann-Whitney U test clarify that the two groups' medians are significantly different in 20 of the 24 cases. The same conclusion can be drawn from the one-sample Wilcoxon test also. ACR is not significantly different from zero for the 3^{rd} to 6^{th} minutes and the closing interval.

We have similar findings for the filter level of 1.5% regarding the time zone of overreaction and reversal effect. For the first minute of the trading day, the magnitude of overreaction is not different from the one found in the 1% filter. However, the reversal effect is huge and almost doubled what we find for lower thresholds. ACR falls to -0.094% in the 1^{st} minute following opening. Then reversal starts, and an upward trend continues until the 45^{th} minutes. It skyrockets to the highest level of 0.426% at that moment. Experiencing a falling towards to closing interval, it rises to the previous high level at closing. Statistical significance of test results is almost the same as reported for 1% filter level.

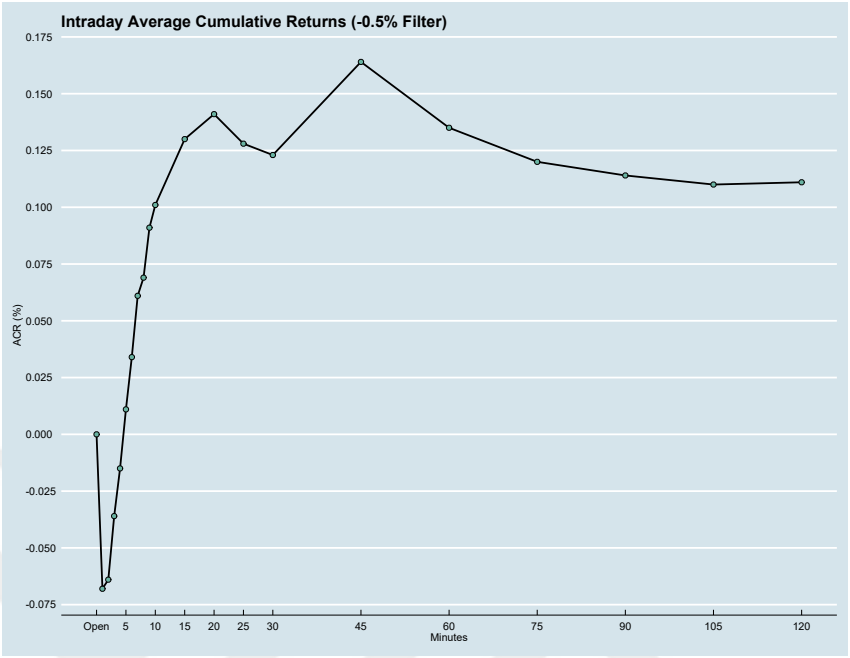
Following negative extreme overnight gaps, overreaction and price reversal exist in the market and are more significant than positive ones. The larger the filter size we apply, the more statistical significance of the results we have. Mean distributions are not the same among event and normal days for any trading zone. Compared to the positive one, overreaction happens with smaller ACR on the negative side, but reversing to the initial opening point occurs more rapidly. It is interesting to see that a huge increase occurs in the last 15 minutes interval for all given filter sizes following negative gaps. General and significant findings for all cases are reported regarding 1^{st} and 2^{nd} minute of trading day where overreaction happens, and reversal begins. Furthermore, both standard deviation and the range of maximum and minimum values of cumulative returns are larger following extreme negative overnight gaps, as seen in Appendix A.

Table 4.2: ACR and Test Results of Event Days After Opening ($|1\%|$ Filter)

Minutes	Filter: +1%					Filter: -1%				
		p-values					p-values			
		One Sample		Two Sample			One Sample		Two Sample	
	ACR(%)	T	W	W's	U	ACR(%)	T	W	W's	U
1	0.108	0 *	0 *	0 *	0 *	-0.092	0 *	0 *	0 *	0 *
2	0.088	0 *	0 *	0 *	0 *	-0.086	0 *	0 *	0 *	0 *
3	0.051	0.011 †	0.011 †	0 *	0.025 †	-0.037	0.192	0.038 †	0 *	0.146
4	0.014	0.534	0.474	0.005 *	0.688	-0.018	0.547	0.299	0 *	0.457
5	-0.008	0.724	0.791	0.004 *	0.508	0.02	0.54	0.578	0 *	0.706
6	-0.039	0.126	0.186	0 *	0.066 ‡	0.045	0.198	0.128	0 *	0.311
7	-0.055	0.038 †	0.055 ‡	0 *	0.014 †	0.082	0.032 †	0.006 *	0 *	0.071 ‡
8	-0.067	0.014 †	0.023 †	0 *	0.005 *	0.089	0.022 †	0.004 *	0 *	0.052 ‡
9	-0.081	0.003 *	0.005 *	0 *	0.001 *	0.108	0.007 *	0.001 *	0 *	0.02 †
10	-0.086	0.003 *	0.004 *	0 *	0.001 *	0.115	0.006 *	0 *	0 *	0.015 †
15	-0.101	0.001 *	0 *	0 *	0.001 *	0.161	0 *	0 *	0 *	0 *
20	-0.106	0.002 *	0.003 *	0 *	0.004 *	0.185	0 *	0 *	0 *	0 *
25	-0.132	0 *	0 *	0 *	0.001 *	0.18	0 *	0 *	0 *	0 *
30	-0.138	0 *	0 *	0 *	0.001 *	0.17	0 *	0 *	0 *	0 *
45	-0.163	0 *	0 *	0.001 *	0.001 *	0.266	0 *	0 *	0 *	0 *
60	-0.148	0 *	0.002 *	0.006 *	0.014 †	0.231	0 *	0 *	0 *	0 *
75	-0.16	0 *	0.002 *	0.009 *	0.026 †	0.22	0 *	0 *	0 *	0 *
90	-0.156	0.001 *	0.007 *	0.038 †	0.074 ‡	0.209	0 *	0 *	0 *	0 *
105	-0.164	0.001 *	0.006 *	0.055 ‡	0.089 ‡	0.189	0.002 *	0 *	0 *	0 *
120	-0.139	0.007 *	0.049 †	0.021 †	0.247	0.2	0.002 *	0 *	0 *	0 *
last60	-0.198	0.035 †	0.134	0.032 †	0.418	0.07	0.537	0.19	0 *	0.101
last30	-0.186	0.062 ‡	0.215	0.009 *	0.637	0.145	0.228	0.056 ‡	0 *	0.022 †
last15	-0.226	0.027 †	0.153	0.013 †	0.556	0.139	0.268	0.073 ‡	0 *	0.018 †
Close	-0.121	0.263	0.868	0.011 †	0.887	0.308	0.019 †	0.003 *	0 *	0.001 *

Note: ACR : Average Cumulative Return; T : T-test; W : Wilcoxon Test; W's : Welch's T-test; U : Mann Whitney U Test

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level



(a) Return Pattern of Event days for the first two hours

(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.4: Daily Return Patterns Following Negative Overnight Gaps (-0.5% Filter)

Table 4.3: ACR and Test Results of Event Days After Opening ($|1.5\%|$ Filter)

Minutes	Filter: +1.5%					Filter: -1.5%				
		p-values					p-values			
		One Sample		Two Sample			One Sample		Two Sample	
	ACR(%)	T	W	W's	U	ACR(%)	T	W	W's	U
1	0.11	0 *	0 *	0 *	0 *	-0.094	0.002 *	0 *	0 *	0.001 *
2	0.078	0.011 †	0.013 †	0 *	0.021 †	-0.07	0.045 †	0.001 *	0 *	0.03 †
3	0.025	0.503	0.481	0.002 *	0.591	-0.011	0.787	0.336	0 *	0.701
4	-0.03	0.46	0.389	0.001 *	0.397	0.014	0.752	0.998	0.005 *	0.835
5	-0.059	0.167	0.168	0 *	0.121	0.057	0.243	0.288	0 *	0.315
6	-0.101	0.028 †	0.028 †	0 *	0.018 †	0.084	0.093 ‡	0.055 ‡	0 *	0.136
7	-0.123	0.011 †	0.012 †	0 *	0.006 *	0.14	0.012 †	0.002 *	0 *	0.022 †
8	-0.136	0.006 *	0.006 *	0 *	0.003 *	0.163	0.004 *	0.001 *	0 *	0.008 *
9	-0.156	0.002 *	0.001 *	0 *	0.001 *	0.173	0.003 *	0 *	0 *	0.006 *
10	-0.167	0.001 *	0 *	0 *	0 *	0.182	0.002 *	0 *	0 *	0.004 *
15	-0.153	0.004 *	0.002 *	0 *	0.003 *	0.229	0 *	0 *	0 *	0 *
20	-0.157	0.006 *	0.009 *	0 *	0.009 *	0.29	0 *	0 *	0 *	0 *
25	-0.174	0.006 *	0.011 †	0 *	0.009 *	0.308	0 *	0 *	0 *	0 *
30	-0.171	0.008 *	0.008 *	0 *	0.016 †	0.294	0 *	0 *	0 *	0 *
45	-0.243	0.001 *	0.001 *	0 *	0.004 *	0.426	0 *	0 *	0 *	0 *
60	-0.242	0.001 *	0.001 *	0 *	0.008 *	0.374	0 *	0 *	0 *	0 *
75	-0.282	0 *	0 *	0 *	0.005 *	0.375	0 *	0 *	0 *	0 *
90	-0.268	0.001 *	0.003 *	0.007 *	0.016 †	0.342	0 *	0 *	0 *	0 *
105	-0.309	0.001 *	0.001 *	0.009 *	0.011 †	0.323	0 *	0 *	0 *	0 *
120	-0.305	0.001 *	0.004 *	0.003 *	0.015 †	0.307	0.001 *	0 *	0 *	0 *
last60	-0.382	0.027 †	0.068 ‡	0.011 †	0.132	0.134	0.445	0.166	0 *	0.152
last30	-0.347	0.06 ‡	0.149	0.01 *	0.26	0.184	0.319	0.123	0 *	0.086 ‡
last15	-0.425	0.024 †	0.076 ‡	0.035 †	0.166	0.19	0.314	0.11	0 *	0.064 ‡
Close	-0.283	0.151	0.603	0.058 ‡	0.461	0.418	0.035 †	0.011 †	0 *	0.006 *

Note: ACR : Average Cumulative Return; T : T-test; W : Wilcoxon Test; W's : Welch's T-test; U : Mann Whitney U Test

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level

4.2 Second Part of Overreaction Hypothesis

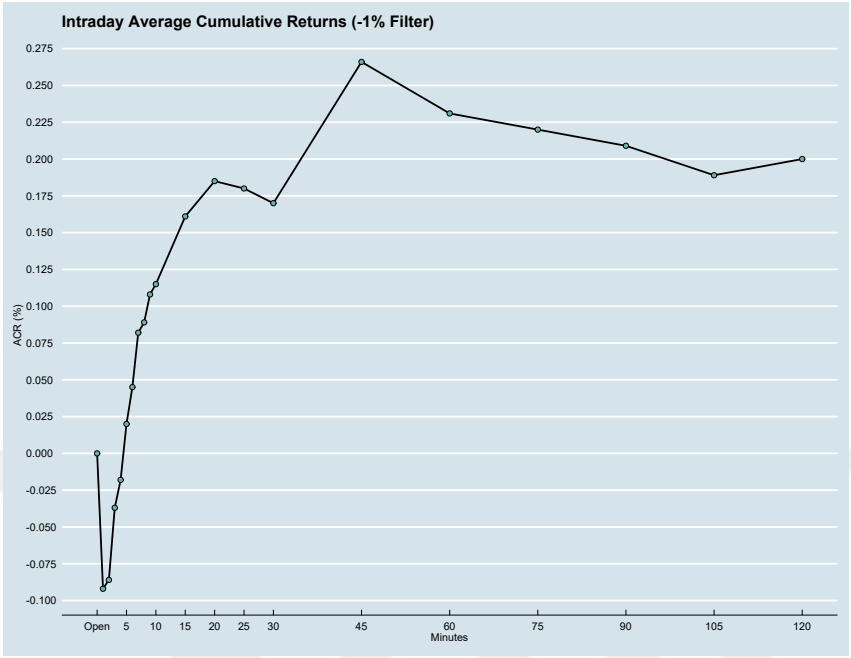
4.2.1 Positive Overnight Gaps

The previous part provides conclusions about the intraday overreaction effect, considering the days whose opening gaps pass the predefined threshold. In this part, we try to look at the magnitude effect from a different perspective by decomposing filter sizes. Each element belongs to just one cluster; thus, each sub-filter size includes different event days.

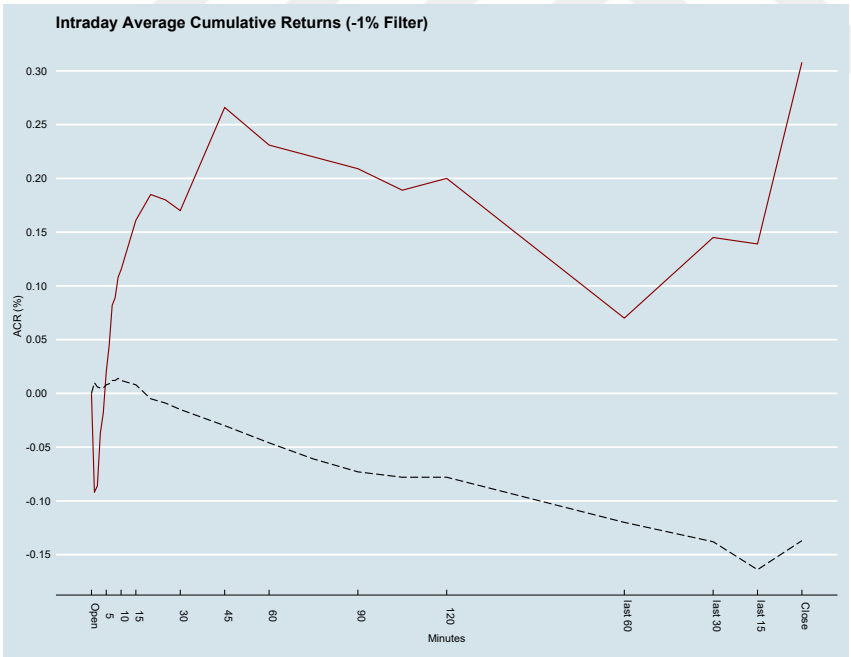
Overreaction and reversals exist for the event days, which experience an overnight gap between 0.5% and 1%. Looking at the Figure 4.7a, the appearance of the phenomenon seems not to change. Overreaction is seen only in the first minute, then reversal appears. However, the process of reversals happens slowly. The index level reverts to its initial position after 30 minutes, whereas it is 7 minutes with the filter level of 0.5% in the first part. Downtrend holds until the last 15 minutes of the trading day, and ACR reaches its minimum of -0.08%. Looking at the Table 4.4, we see that means of event days return are significantly different from zero, mostly in the first seven minutes of the trading day. The shape of the distribution between the event and normal days is not similar in the first five minutes, according to parametric and non-parametric test results.

Analyzing the group of days whose overnight gap is in the range between 1% and 1.5%, one can see in Figure 4.8b that the configuration of ACRs is not the same as observed in the previous part. Overreaction exists in the first minute, then ACR slumps to its minimum of -0.112% in 30 minutes. It starts to rise again after that and follows up and down movements throughout the day. ACR has a positive value at closing. We have significant results for the first four minutes from all statistical tests as seen in Table 4.5. Considering the last hour of the trading day, both parametric and non-parametric test results confirm that the mean and median of cumulative returns are not significantly different from zero.

Studying sub-filter sizes provides robust evidence about intraday overreaction and reversal effect for BIST 100 index. When we compare the results of the sub-filter

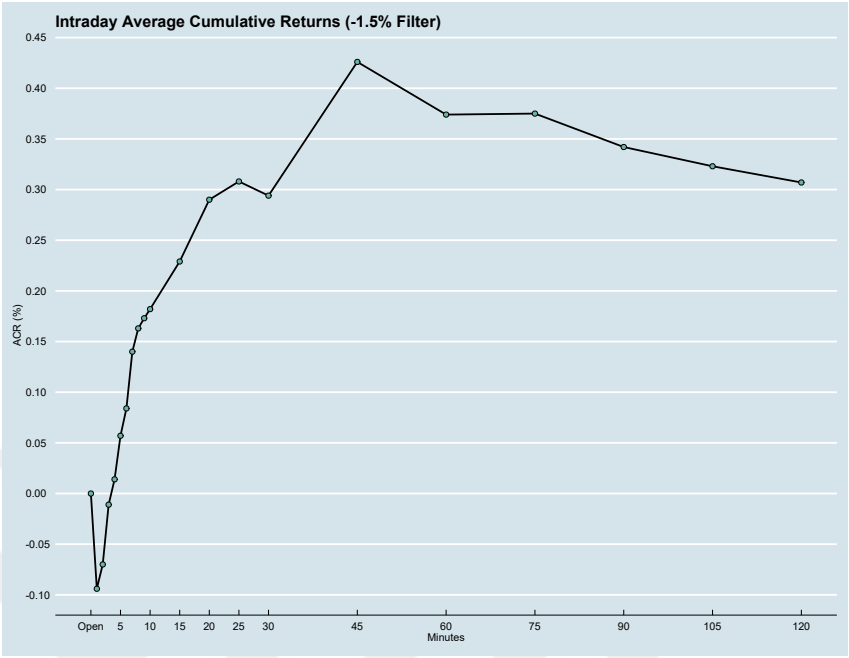


(a) Return Pattern of Event days for the first two hours

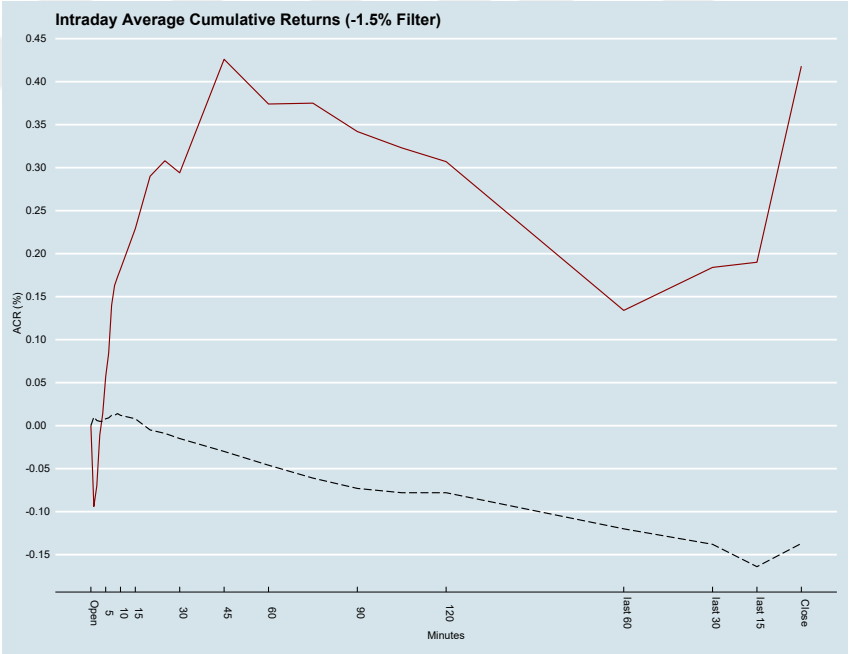


(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.5: Daily Return Patterns Following Negative Overnight Gaps (-1% Filter)



(a) Return Pattern of Event days for the first two hours



(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.6: Daily Return Patterns Following Negative Overnight Gaps (-1.5% Filter)

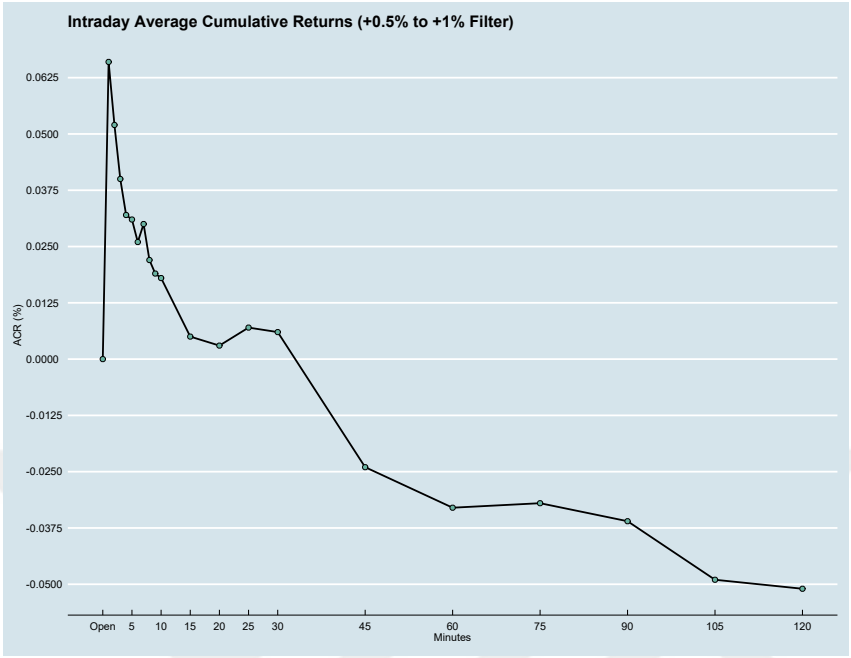
range between 0.5% to 1% and 1.5% filter levels, the magnitude effect is clearly seen. If the market increase by 0.5% to 1% at the opening, the reversal effect is relatively limited. If it climbs by 1.5% or more, however, the pace and amplitude of reversal become enormous. Furthermore, we witness a larger standard deviation and improved significance results with high filter levels. Note that the market does not fall behind the line, belongs to non-event days, and closes near its initial point in case of lower filters. On the other hand, the ACR line belongs to a filter of 1.5% shows a steady downtrend and is far below the line of non-event days as seen in Figure 4.3b. The closing value of ACR is also relatively low, below -0.25%, for the days experience an opening gap of 1.5% or more.

Table 4.4: ACR and Test Results of Event Days After Opening (Second Part)

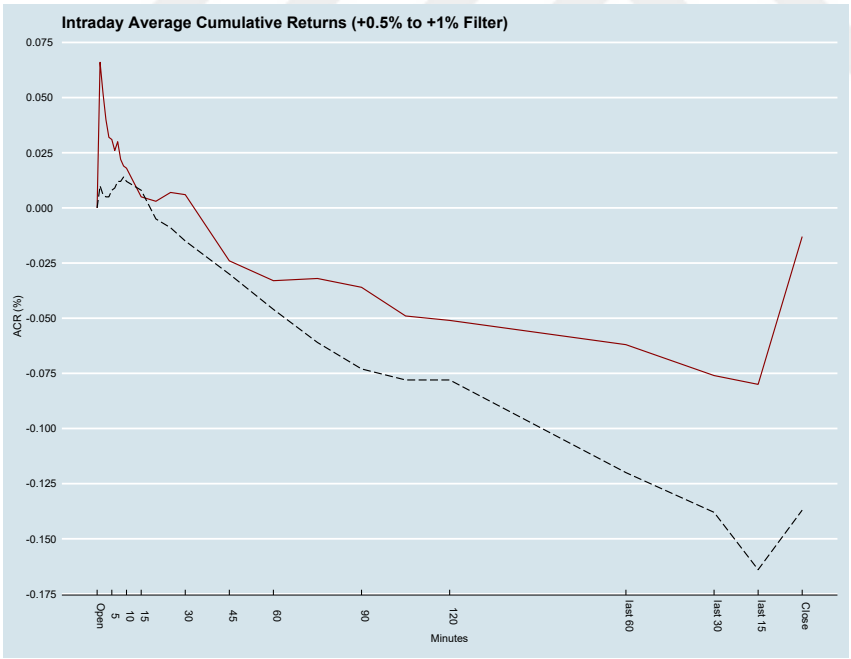
Minutes	Filter: +0.5% to +1%					Filter: -0.5% to -1%				
		p-values					p-values			
		One Sample		Two Sample			One Sample		Two Sample	
	ACR(%)	T	W	W's	U	ACR(%)	T	W	W's	U
1	0.066	0 *	0 *	0 *	0 *	-0.048	0 *	0 *	0 *	0 *
2	0.052	0 *	0 *	0 *	0 *	-0.045	0.002 *	0.002 *	0 *	0.001 *
3	0.04	0 *	0 *	0 *	0.001 *	-0.035	0.052 ‡	0.048 †	0 *	0.032 †
4	0.032	0.001 *	0 *	0.002 *	0.016 †	-0.011	0.57	0.521	0.031 †	0.438
5	0.031	0.006 *	0 *	0.006 *	0.065 ‡	0.003	0.889	0.689	0.02 †	0.838
6	0.026	0.033 †	0 *	0.021 †	0.204	0.025	0.284	0.113	0.008 *	0.504
7	0.03	0.019 †	0 *	0.044 †	0.201	0.044	0.07 ‡	0.016 †	0.001 *	0.202
8	0.022	0.103	0.003 *	0.209	0.516	0.052	0.044 †	0.01 *	0 *	0.139
9	0.019	0.18	0.005 *	0.26	0.738	0.077	0.002 *	0.001 *	0 *	0.015 †
10	0.018	0.216	0.006 *	0.203	0.726	0.089	0.001 *	0 *	0 *	0.004 *
15	0.005	0.765	0.028 †	0.432	0.834	0.103	0 *	0 *	0 *	0.001 *
20	0.003	0.855	0.047 †	0.165	0.647	0.104	0.001 *	0 *	0 *	0 *
25	0.007	0.669	0.035 †	0.08 ‡	0.394	0.084	0.009 *	0.001 *	0 *	0.005 *
30	0.006	0.753	0.056 ‡	0.067 ‡	0.286	0.083	0.013 †	0.002 *	0 *	0.004 *
45	-0.024	0.263	0.954	0.502	0.788	0.077	0.036 †	0.007 *	0 *	0.005 *
60	-0.033	0.16	0.803	0.332	0.596	0.053	0.16	0.039 †	0 *	0.012 †
75	-0.032	0.194	0.811	0.146	0.292	0.035	0.379	0.096 ‡	0 *	0.021 †
90	-0.036	0.171	0.715	0.076 ‡	0.202	0.033	0.428	0.171	0 *	0.015 †
105	-0.049	0.082 ‡	0.397	0.162	0.332	0.043	0.335	0.116	0 *	0.009 *
120	-0.051	0.09 ‡	0.449	0.184	0.426	0.036	0.463	0.127	0 *	0.025 †
last60	-0.062	0.194	0.589	0.118	0.266	-0.034	0.692	0.919	0.018 †	0.33
last30	-0.076	0.148	0.524	0.093 ‡	0.27	-0.022	0.804	0.781	0.024 †	0.208
last15	-0.08	0.151	0.535	0.044 †	0.156	-0.064	0.48	0.875	0.127	0.29
Close	-0.013	0.826	0.638	0.011 †	0.048 †	0.052	0.587	0.365	0.028 †	0.059 ‡

Note: ACR : Average Cumulative Return; T : T-test; W : Wilcoxon Test; W's : Welch's T-test; U : Mann Whitney U Test

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level

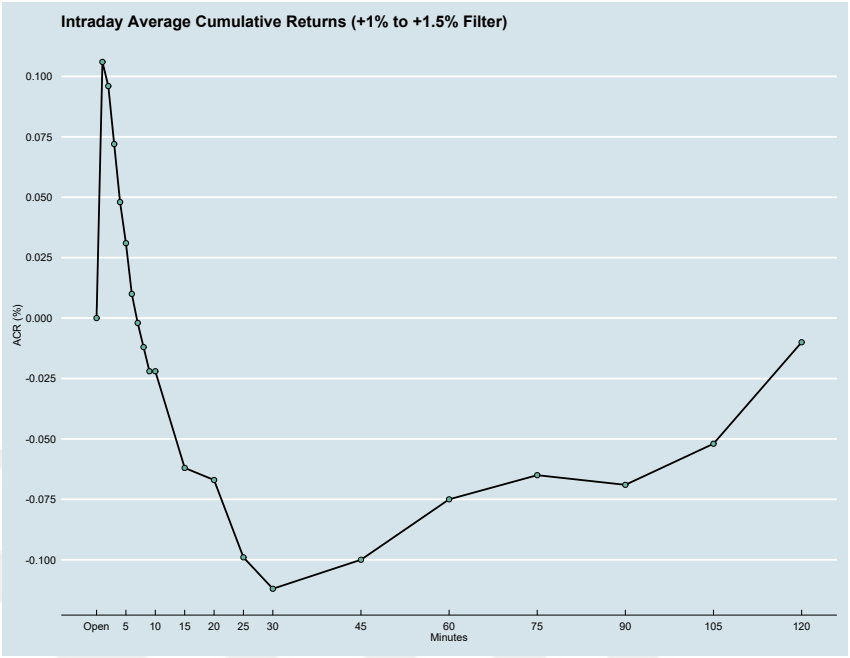


(a) Return Pattern of Event days for the first two hours

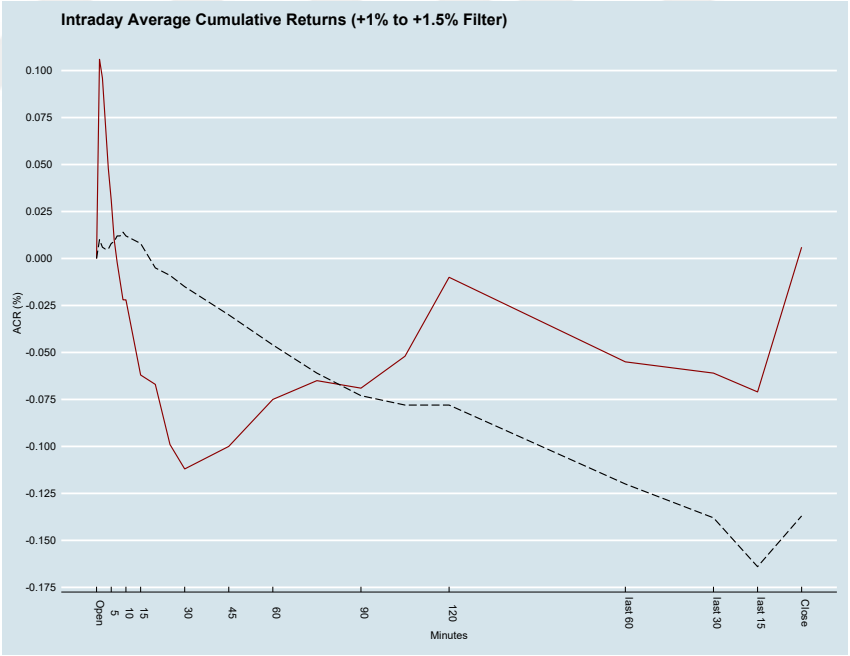


(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.7: Daily Return Patterns Following Positive Overnight Gaps (0.5% to 1%)



(a) Return Pattern of Event days for the first two hours



(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.8: Daily Return Patterns Following Positive Overnight Gaps (1% to 1.5%)

Table 4.5: ACR and Test Results of Event Days After Opening (Second Part)

Minutes	Filter: +1% to +1.5%					Filter: -1% to -1.5%				
		p-values					p-values			
		One Sample		Two Sample			One Sample		Two Sample	
	ACR(%)	T	W	W's	U	ACR(%)	T	W	W's	U
1	0.106	0 *	0 *	0 *	0 *	-0.089	0.001 *	0 *	0 *	0 *
2	0.096	0 *	0 *	0 *	0 *	-0.108	0.001 *	0 *	0 *	0.001 *
3	0.072	0.001 *	0.002 *	0.027 †	0.002 *	-0.071	0.046 †	0.039 †	0 *	0.035 †
4	0.048	0.048 †	0.047 †	0.003 *	0.08 ‡	-0.062	0.137	0.121	0.001 *	0.112
5	0.031	0.222	0.262	0.08 ‡	0.368	-0.028	0.519	0.664	0.03 †	0.415
6	0.01	0.696	0.557	0.349	0.962	-0.008	0.865	0.958	0.034 †	0.717
7	-0.002	0.954	0.96	0.161	0.631	0.003	0.95	0.67	0.058 ‡	0.851
8	-0.012	0.677	0.893	0.137	0.407	-0.01	0.845	0.837	0.028 †	0.66
9	-0.022	0.468	0.662	0.131	0.253	0.021	0.69	0.276	0.044 †	0.887
10	-0.022	0.501	0.864	0.138	0.304	0.025	0.662	0.247	0.013 †	0.826
15	-0.062	0.095 ‡	0.086 ‡	0.008 *	0.064 ‡	0.07	0.211	0.06 ‡	0.001 *	0.274
20	-0.067	0.099 ‡	0.131	0.045 †	0.135	0.044	0.442	0.199	0.007 *	0.394
25	-0.099	0.009 *	0.011 †	0.003 *	0.02 †	0.007	0.901	0.489	0.09 ‡	0.787
30	-0.112	0.003 *	0.004 *	0.004 *	0.012 †	0.002	0.968	0.667	0.21	0.762
45	-0.1	0.015 †	0.09 ‡	0.208	0.094 ‡	0.052	0.41	0.202	0.039 †	0.201
60	-0.075	0.083 ‡	0.246	0.472	0.493	0.038	0.57	0.276	0.01 *	0.214
75	-0.065	0.164	0.372	0.876	0.925	0.012	0.87	0.507	0.06 ‡	0.326
90	-0.069	0.16	0.363	0.724	0.933	0.03	0.707	0.344	0.018 †	0.203
105	-0.052	0.322	0.489	0.484	0.598	0.01	0.908	0.573	0.068 ‡	0.313
120	-0.01	0.857	0.875	0.118	0.198	0.056	0.559	0.258	0.009 *	0.168
last60	-0.055	0.578	0.747	0.051 ‡	0.524	-0.016	0.895	0.91	0.142	0.409
last30	-0.061	0.558	0.727	0.088 ‡	0.468	0.091	0.493	0.318	0.038 †	0.093 ‡
last15	-0.071	0.513	0.788	0.168	0.407	0.07	0.638	0.447	0.047 †	0.125
Close	0.006	0.963	0.797	0.086 ‡	0.236	0.162	0.307	0.18	0.013 †	0.065 ‡

Note: ACR : Average Cumulative Return; T : T-test; W : Wilcoxon Test; W's : Welch's T-test; U : Mann Whitney U Test

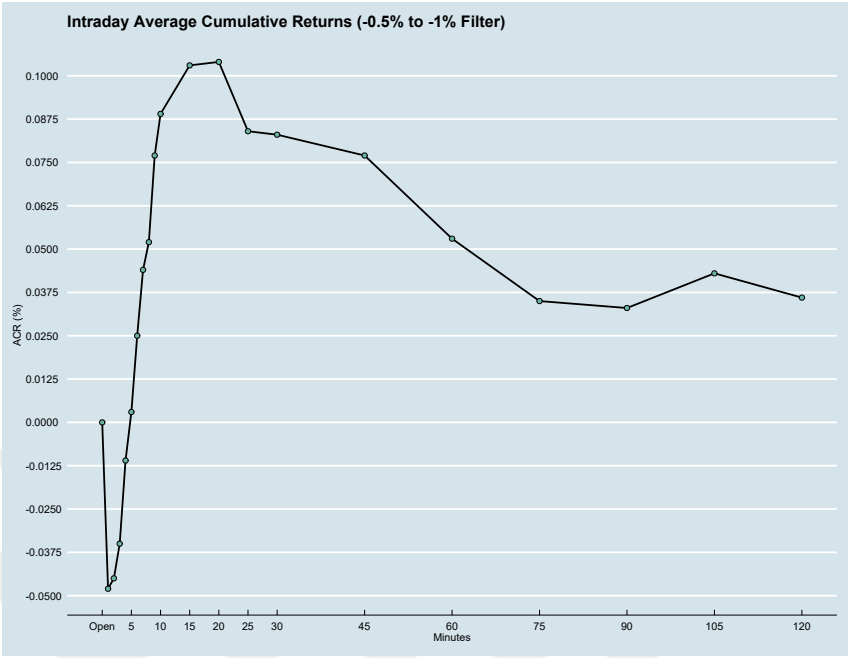
Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level

4.2.2 Negative Overnight Gaps

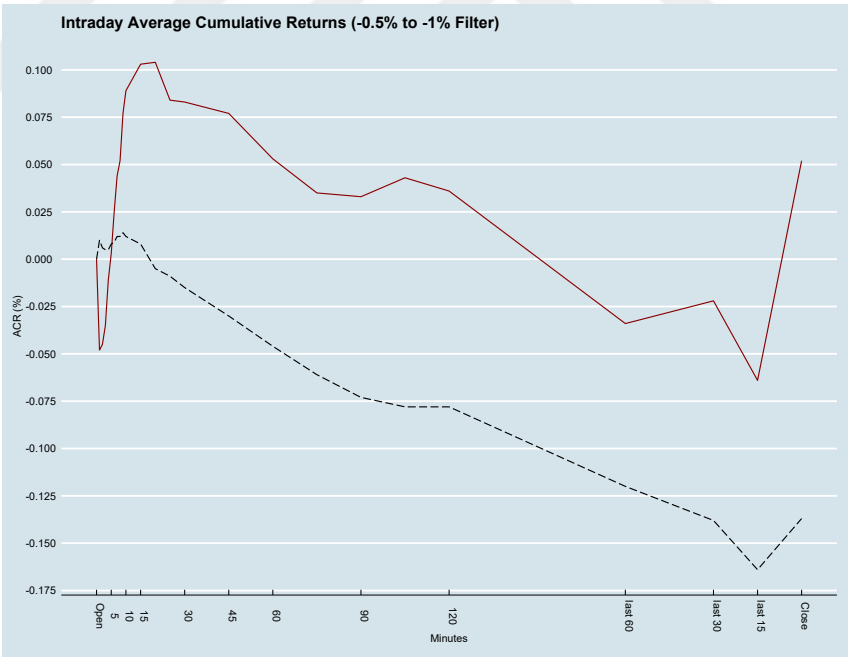
Overreaction exists and lasts for one minute following opening gaps with a range from -1% to -0.5%. The market experiences a positive spike in a short time as 15 minutes, and ACR moves to 0.103%. The downward trend begins after that, and the ACR declines to -0.064%, even less than the point at the first minute. It trends up from there and moves above 0.05% at closing. The Figure 4.9b shows that intraday return following negative opening gaps is higher than the return in normal days. Although they have similar return routines throughout the day, the difference between return in event days and non-event days is approximately 0.1%. In addition, there is not much different between Figures 4.4b and 4.9b regarding configurations of return pattern. Looking at the Table 4.4, we see highly significant p-values from Welch's t-test. The mean of cumulative returns is not equal among events and normal days at any point except at the last 15 minutes of the trading day. According to the one-sample t-test, the null hypothesis is rejected for most cases in the first 45 minutes. Similar significant results also hold for the one-sample Wilcoxon test. The U test confirms significant results for 15 out of 20 cases in the first 120 minutes.

When we consider the filter range from -1% to -1.5%, Figure 4.10a and Table 4.5 show consistency with short-term overreaction hypothesis. However, the results diverge from the others as market participants overreact to information in the first two minutes. At the second minute, ACR reaches to -0.108%, then reverts to 0.07% in 15 minutes. It experiences up and down deviations after that and moves around zero until the last hour of the trading day. The highest point of it is seen at closing, 0.162%. It is interesting to see that the reversal effect is limited, and ACR reaches a smaller value than that in the lower sub-filter level. Test results say that we can reject the null hypothesis in the first three minutes. We have consistent results from one sample parametric and non-parametric tests. We can not reject the null hypothesis for almost all of the cases after three minutes in both tests. Welch's t-test reports that cumulative returns of event days are significantly different from normal days in 22 out of 24 cases. On the contrary, we have less significant p-values from the non-parametric U test. Apart from the first three minutes, the only significant results to reject the null hypothesis are to hold for the closing intervals.

The choice of using sub-filters and clustering event days does not change our main conclusion that short-term overreaction exists in Borsa Istanbul and happens in the first minutes of the trading day. Studying several sizes of gaps, we clearly report that the particular effect of the extreme gaps on return patterns occurs within half an hour following opening. In most cases, the correction begins at the second minute, and significant p-values are reported from all statistical tests regarding the first two minutes. In general, the magnitude of overreaction is limited regardless of filter size due to its lack of duration. The reversal effect, however, tends to rise proportional to gap size. An interesting finding related to negative gaps is that whenever the market opens with an extreme negative price change, the index experiences a remarkable uptrend at the last 15 minutes of the trading day. This uptrend is significantly different from normal days and grows with a larger threshold. By clustering, we obtain more precision evidence for the magnitude effect of the short-term overreaction phenomenon.

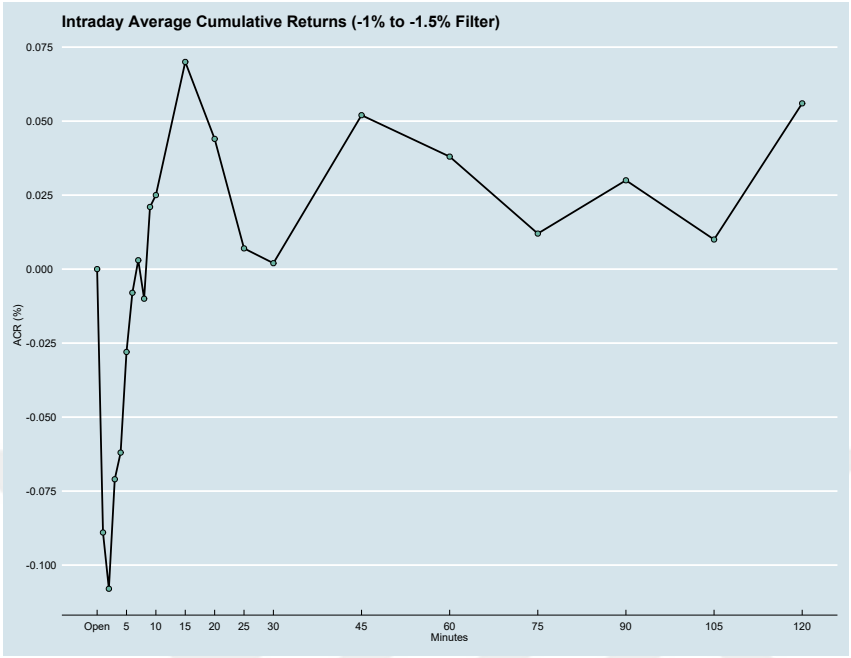


(a) Return Pattern of Event days for the first two hours

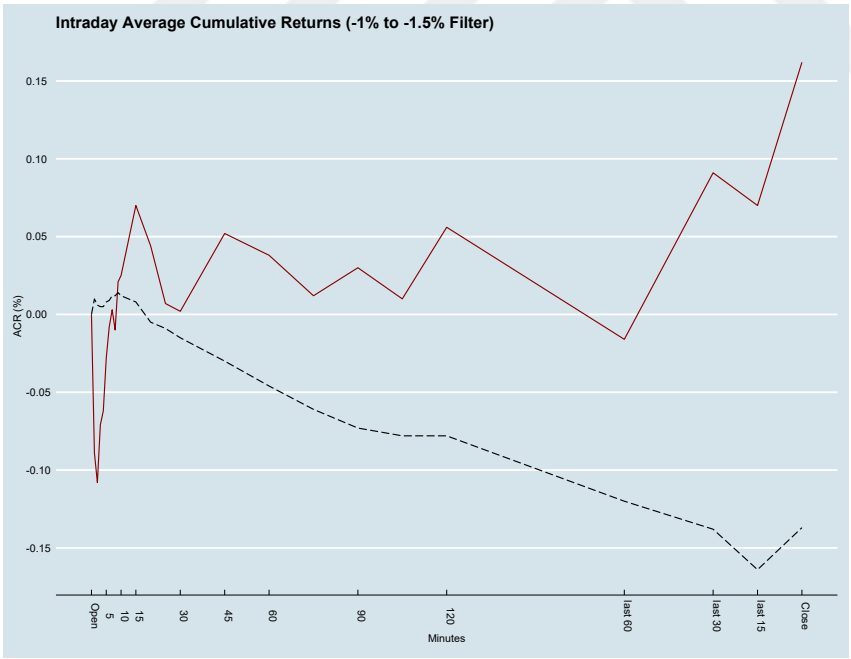


(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.9: Daily Return Patterns Following Positive Negative Gaps (-0.5% to -1%)



(a) Return Pattern of Event days for the first two hours



(b) Comparison of Return Patterns Between Event Days (Solid Line) and Normal Days (Dashed line)

Figure 4.10: Daily Return Patterns Following Positive Negative Gaps (-1% to -1.5%)

CHAPTER 5

CONCLUSION

Some of the studies in the literature have documented the existence of short-term overreaction and subsequent price reversals. Most famous and old ones are done by Fung et al. [30] and Grant et al. [34]. The issue has been analyzed over the developed countries, mostly in the U.S. markets. Financial markets are expected to be more efficient thanks to the improvements in technology innovations and financial globalization. However, the study, using relatively recent historical data for the U.S. market, showed that the phenomenon still exists in the modern finance world (Stubinger and Schneider [64]). This study aims to present an evidence for the intraday overreaction hypothesis with an emerging and little examined market.

Our long-term study reports significant overreaction and price reversal effects following large overnight price gaps. Examining the Turkish stock market's intraday return patterns after extreme movements, we document consistent results with previous literature. In the light of key findings, price continuation lasts only one minute after opening; then, we witness the reign of a severe reversal trend until the first 45 minutes. Although our main conclusions go along with the results of previous related studies whose findings point out the temporary anomaly and shortly reversal [30, 34, 64, 68], peculiarities of return pattern displays disparity from other markets. Price continuation following large morning gaps in BIST lasts a shorter time, and reverting towards to initial opening level takes less time. For example, in the study of Grant et al. [34], the overreaction effect proceeds 10 minutes and converging to the initial point happens after 15 minutes. A proximate finding of a relatively new study conducted by Stubinger and Schneider [64] in the year 2019, however, reports that

reversal behavior following negative morning gaps begins in 2 minutes after opening. In the first part, we provide coherent results for all filter sizes that index moves for a minute in the same direction, then corrections begin at the second minute and index falls below its initial level within ten minutes. Thus, we can draw an inference based on the recent studies that the duration of intraday overreaction becomes shorter in the course of time; however, this inference would be doubtful due to the paucity of studies.

Some papers have investigated investor types' role while examining the initial overreaction effect or volatility pattern [29, 39, 33]. Fung and Lam [29] concluded that overreaction tends to be short-lived if supported by a few irrational investors. In favor of that, Güner and Önder [33] attributed higher volatility in the morning to noise-related trades rather than informational. They also said that prices would have reversed quickly in case of noise-related movements. Although it is beyond the scope of this thesis, a few irrational traders may give rise to the initial short-lived overreaction effect on BIST, which our findings point out to.

Another remark observed from the figures is that some deviations exist between the event and normal days, mostly during the first minutes. As a supportive of figures, highly significant p-values for the first minutes of trading days are reported by two-sample statistical test results. Therefore, a strong initial overreaction and reversal effect exists on BIST in the light of these pieces of evidence. The effect of corrections lasts for the first 45 minutes in event days. The market then becomes calm throughout the day until the closing interval. The market experiences upswing accelerated in the last 15 minutes before closing, and it is true for both positive and negative gap scenarios. The findings related to deviations in the morning are consistent with the results of Kang [40] and Bildik [12]. Both studies link this to an excessive amount of information accumulated. Relatively extreme movements around the opening and closing session are also in line with the paper of Ekinci [26], which documents that large amounts of orders are traded in the first 20 minutes following the openings and just before closings in the Turkish stock market. On the contrary to the result of Grant et al. [34] in which ACR of S&P 500 converges to the zero at closing for the days following overnight gaps, ACR of BIST 100 in the event days is above (below) zero at closing in case of negative (positive) morning gaps.

Looking at the configurations of the return pattern for various filter sizes, the conclusions are similar. Price continuation following opening is limited. The magnitude of subsequent reversals, however, positively depends on the filter size. Besides that, the level of initial price changes has an impact on ACR at closing. We observe lower ACR at closing as filter level increases for positive scenarios and higher ACR for negative scenarios. To provide robust evidence for the hypothesis of DeBondt and Thaler [21] related to magnitude effect, event days are clustered by decomposition of filter levels. Even though clustering does not change our main conclusion, the pace and amplitude of the reversal effect are more clearly reported. Thus, the findings for magnitude effect are consistent with the ones documented by Holmberg et al. [35]. Also, note that converging to the initial opening level happens in a shorter duration with a larger filter size.

The correction reactions of investors to the negative overnight gap are more strong and significant than positive ones. Reversing to the initial point occurs more rapidly, and ACR ramps higher and faster following a negative gap. Another remark observed is an upswing shift in the last 15 minutes for both scenarios. In the case of negative gaps, however, it is considerably much higher. Figures also show the difference between the return patterns of event days experiencing positive and negative gaps. In the case of a positive gap, it displays a steady drop and a downward trend throughout the trading day. On the other hand, in the case of a negative gap, retracements are observed following the correction. As a last remark, both standard deviation and the range of maximum and minimum values of cumulative returns are larger following negative overnight gaps than those of positive overnight gaps, which is in line with the findings of Stubinger and Schneider [64].

We credence the literature by providing evidence from an emerging and little examined market that short-term overreaction anomaly still exists. Although Berkman et al. [11] report that the short-term overreaction is observed mainly for non-actively traded stocks and the stocks that vulnerable to arbitrage, we may document a contrary finding by considering BIST 100, which includes most liquid stocks in the Turkish stock market. Moreover, this thesis's findings may contribute to the discussions regarding the efficiency of emerging stock markets and investors who seek a potentially rewarding short-term strategy. In the future, this study should be improved by ex-

amining individual stocks based on their sector or size. Investigating this issue by weekdays can also be considered as a future study. Furthermore, a simulation of a strategy based on these findings can be executed to test whether a considerable return would be gained.

REFERENCES

[1] G. A. Akerlof and R. J. Shiller, *Animal Spirits: How Human Psychology Drives the Economy and Why It Matters for Global Capitalism*, Princeton University Press, 2009.

[2] D. Alper and E. Aydoğan, The Profitability of Contrarian Strategy: Borsa Istanbul Case, Muhasebe ve Finansman Dergisi, 74, pp. 201–214, 2017.

[3] A. Antoniou, E. C. Galariotis, and S. I. Spyrou, Short–term Contrarian Strategies in the London Stock Exchange: Are They Profitable? Which Factors Affect Them?, Journal of Business Finance and Accounting, 33, pp. 839–867, 2006.

[4] A. B. Atkins and E. A. Dyl, Price reversals, bid–ask spreads, and market efficiency, Journal of Financial and Quantitative Analysis, 25(4), pp. 535–547, 1990.

[5] M. Baker and J. Wurgler, Investor sentiment and the cross–section of stock returns, The journal of Finance, 61(4), pp. 1645–1680, 2006.

[6] O. Barak, İMKB'de Aşırı Reaksiyon Anomalisi Ve Davranışsal Finans Modelleri Kapsaminda Değerlendirilmesi, Gazi Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 10(1), pp. 207–229, 2008.

[7] N. Barberis, Psychology–based models of asset prices and trading volume, Handbook of Behavioral Economics: Applications and Foundations 1, 1, pp. 79–175, 2018.

[8] N. Barberis, A. Shleifer, and R. Vishny, A model of investor sentiment, Journal of financial economics, 49(3), pp. 307–343, 1998.

[9] U. Basdas and A. Oran, Event studies in Turkey, Borsa Istanbul Review, 14(3), pp. 167–188, 2014.

[10] A. Baytas and N. Cakici, Do markets overreact: International evidence, Journal of Banking and Finance, 23(7), pp. 1121–1144, 1999.

[11] H. Berkman, P. D. Koch, L. Tuttle, and Y. J. Zhang, Paying attention: Overnight returns and the hidden cost of buying at the open, Journal of Financial and Quantitative Analysis, 47(4), pp. 715–741, 2012.

[12] R. Bildik, Intra–day seasonalities on stock returns: Evidence from the Turkish Stock Market, Emerging Markets Review, 2(4), pp. 387–417, 2001.

[13] R. Bildik and G. Gülay, Profitability of contrarian strategies: Evidence from the Istanbul stock exchange, International Review of Finance, 7, pp. 61–87, 2007.

[14] G. M. Caporale and A. Plastun, Price gaps: Another market anomaly?, Investment Analysts Journal, 46(4), pp. 279–293, 2017.

[15] K. C. Chan, On the contrarian investment strategy, Journal of Business, pp. 147–163, 1988.

[16] N. Chopra, J. Lakonishok, and J. R. Ritter, Measuring abnormal performance: Do stocks overreact?, Journal of Financial Economics, 31(2), pp. 235–268, 1992.

[17] J. Conrad, M. N. Gultekin, and G. Kaul, Profitability of short–term contrarian strategies: Implications for market efficiency, Journal of Business and Economic Statistics, 15(3), pp. 379–386, 1997.

[18] M. Cooper, D. David, and P. Gary, Real estate securities and a filter–based, short–term trading strategy, Journal of Real Estate Research, 18(2), pp. 313–333, 1999.

[19] C. J. Corrado, Event studies: A methodology review, Accounting and Finance, 51(1), pp. 207–234, 2011.

[20] D. R. Cox and D. R. Peterson, Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance, The Journal of Finance, 49(1), pp. 255–267, 1994.

[21] W. F. M. De Bondt and R. H. Thaler, Does the stock market overreact?, The Journal of finance, 40(3), pp. 793–805, 1985.

[22] P. Della Corte, R. Kosowski, and T. Wang, Market Closure and Short–Term Reversal, in *Asian Finance Association (AsianFA) 2016 Conference*, 2015.

[23] H. I. Dizdarlar and C. Reyhan, Aşırı Tepki Hipotezinin Geçerliliğinin Test Edilmesi: Borsa İstanbul Üzerine Bir Araştırma, Uluslararası İktisadi ve İdari İncelemeler Dergisi, pp. 815–832, 2017.

[24] H. Doğukanlı, G. Vural, and B. Ergün, Using Various Portfolio Formation and Test Periods: An Examination of Overreaction in ISE, Associate Editors Board Academicians, 13(49), 2012.

[25] D. Easley and M. O'hara, Time and the process of security price adjustment, The Journal of finance, 47(2), pp. 577–605, 1992.

[26] C. Ekinci, A statistical analysis of intraday liquidity, returns and volatility of an individual stock from the Istanbul stock exchange, SSRN Electronic Journal, 2003.

[27] E. F. Fama, The behavior of stock–market prices, The journal of Business, 38(1), pp. 34–105, 1965.

[28] F. D. Foster and S. Viswanathan, A theory of the interday variations in volume, variance, and trading costs in securities markets, The Review of Financial Studies, 3(4), pp. 593–624, 1990.

[29] A. K. W. Fung and K. Lam, Overreaction of index futures in Hong Kong, Journal of Empirical Finance, 11(3), pp. 331–351, 2004.

[30] A. K. W. Fung, D. M. Y. Mok, and K. Lam, Intraday price reversals for index futures in the US and Hong Kong, Journal of Banking and Finance, 24(7), pp. 1179–1201, 2000.

[31] C. Gaunt, Overreaction in the Australian equity market: 1974-1997, Pacific–Basin Finance Journal, 8, pp. 375–398, 2000.

[32] L. R. Glosten and P. R. Milgrom, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, Journal of financial economics, 14(1), pp. 71–100, 1985.

[33] N. Güner and Z. Önder, Information and volatility: Evidence from an emerging market, Emerging Markets, Finance and Trade, 38(6), p. 26, 2002.

[34] J. L. Grant, A. Wolf, and S. Yu, Intraday price reversals in the US stock index futures market: A 15–year study, Journal of Banking and Finance, 29(5), pp. 1311–1327, 2005.

[35] U. Holmberg, C. Lonnbark, and C. Lundstrom, Assessing the profitability of intraday opening range breakout strategies, Finance Research Letters, 10(1), pp. 27–33, 2013.

[36] A. C. Inci, Accentuated intraday volatility in emerging markets: The Turkish stock exchange, Journal of International Finance Studies, 12, pp. 37–52, 2012.

[37] A. C. Inci and D. Ozenbas, Intraday volatility and the implementation of a closing call auction at Borsa Istanbul, Emerging Markets Review, 33, pp. 79–89, 2017.

[38] D. Kahneman and A. Tversky, *Intuitive prediction: Biases and corrective procedures*, Cambridge University Press, 1977.

[39] J. Kang, M. H. Liu, and S. X. Ni, Contrarian and momentum strategies in the China stock market: 1993-2000, Pacific–Basin Finance Journal, 10(3), pp. 243–265, 2002.

[40] W. Kang, A study of intraday returns, Available at SSRN 618983, 2005.

[41] M. B. Karan and a. A. Tarım, İMKB'de Hisse Senedi Getirilerinin Aşırı Tepkisi Üzerinde Ampirik Bir İnceleme, Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 19(1), pp. 29–46, 2001.

[42] G. Kaul and M. Nimalendran, Price reversals : Bid–ask errors or market overreaction?, Journal of Financial Economics, 28, pp. 67–93, 1990.

[43] S. Klossner, M. Becker, and R. Friedmann, Modeling and measuring intraday overreaction of stock prices, Journal of Banking and Finance, 36(4), pp. 1152–1163, 2012.

[44] L. Kryzanowski and H. Zhang, The contrarian investment strategy does not work in Canadian markets, Journal of Financial and Quantitative Analysis, 27(3), pp. 383–395, 1992.

[45] A. S. Kyle, Continuous auctions and insider trading, Econometrica: Journal of the Econometric Society, pp. 1315–1335, 1985.

[46] V. Lalwani, U. Sharma, and M. Chakraborty, Investor reaction to extreme price shocks in stock markets: A cross country examination, IIMB Management Review, 31(3), pp. 258–267, 2019.

[47] S. J. Larson and J. Madura, What drives stock price behavior following extreme one–day returns, Journal of Financial Research, 26(1), pp. 113–127, 2003.

[48] B. N. Lehmann, Fads, martingales, and market efficiency, The Quarterly Journal of Economics, 105(1), pp. 1–28, 1990.

[49] C. H. Lin, H. Hsu, and C. Y. Chiang, Trading patterns and performance of trader types in Taiwan futures market, Review of pacific Basin Financial markets and Policies, 8(02), pp. 217–234, 2005.

[50] D. Maher and A. Parikh, Short–term under/overreaction, anticipation or uncertainty avoidance? Evidence from India, Journal of International Financial Markets, Institutions and Money, 21(4), pp. 560–584, 2011.

[51] T. H. McInish, D. K. Ding, C. S. Pyun, and U. Wongchoti, Short–horizon contrarian and momentum strategies in Asian markets: An integrated analysis, International review of financial analysis, 17(2), pp. 312–329, 2008.

[52] M. J. L. Miralles, Q. J. L. Miralles, and Q. M. M. Miralles, Intraday stock market behavior after shocks: The importance of bull and bear markets in Spain, Journal of Behavioral Finance, 15(2), pp. 144–159, 2014.

[53] K. Miwa and K. Ueda, Is the Extension of Trading Hours Always Beneficial? An Artificial Agent-Based Analysis, Computational Economics, 2015.

[54] J. C. Mun, G. M. Vasconcellos, and R. Kish, Tests of the contrarian investment strategy evidence from the French and German stock markets, International Review of Financial Analysis, 8(3), pp. 215–234, 1999.

[55] J. C. Mun, G. M. Vasconcellos, and R. Kish, The contrarian/overreaction hypothesis: An analysis of the US and Canadian stock markets, Global Finance Journal, 11, pp. 53–72, 2000.

[56] U. Numan and K. Andonov, Reversal of Monday returns, Quantitative Finance, 16(4), pp. 649–665, 2016.

[57] S. Oncu, H. Aktas, S. Kargin, R. Aktas, and N. Kayali, The stock market reaction to extreme events: The evidence from Turkey, International Research Journal of Finance and Economics, 6(6), pp. 78–85, 2006.

[58] G. S. Parikakis and T. Syriopoulos, Contrarian strategy and overreaction in foreign exchange markets, Research in International Business and Finance, 22(3), pp. 319–324, 2008.

[59] O. Plastun and R. Mynhardt, The overreaction hypothesis: The case of Ukrainian stock market, Mynhardt, RH, Plastun, A." The overreaction hypothesis: The case of Ukrainian stock market" Corporate Ownership and Control, 11(1), pp. 406–422, 2013.

[60] A. Polat, T. Yucel, and H. Kose, The Reaction of Abnormal Returns to The Large Stock Market Shocks. Evidence From Borsa Istanbul Sport Index, Proceedings of The 7th MAC 2016, 2016.

[61] J. M. Poterba and L. H. Summers, Mean reversion in stock prices: Evidence and implications, Journal of financial economics, 22(1), pp. 27–59, 1988.

[62] A. M. Poteshman, Underreaction, overreaction, and increasing misreaction to information in the options market, The Journal of Finance, 56(3), pp. 851–876, 2001.

[63] R. J. Shiller, Irrational Exuberance Princeton, Prunceton University Paper, 2000.

[64] J. Stubinger and L. Schneider, Statistical Arbitrage with Mean–Reverting Overnight Price Gaps on High–Frequency Data of the S&P 500, The journal of Risk and Financial Management, 12(2), 2019.

[65] M. Tetik and E. Özen, Overreaction Hypothesis and Reaction of Borsa Istanbul to Dow–Jones, Business and Economic Research, 6(2), 2016.

[66] V. Tripathi and S. Aggarwal, Prior Return Effect in Indian Stock Market: An Intra–Day Analysis, International Journal of Financial Management, 5(1), pp. 33–56, 2015.

[67] K. D. Uulu, Menkul Kiymet Borsalarinda Buyuk Fiyat Degisimleri: Borsa Istanbul Uzerine Bir Uygulama, Hacettepe University, 2018.

[68] J. H. Venter, Intraday momentum and contrarian effects on the JSE, Investment Analysts Journal, 38(70), pp. 47–60, 2009.

[69] T. Yücel and F. D. Taşkin, Aşırı tepki hipotezi ve İstanbul Menkul Kıymetler Borsası'ndan kanıtlar, Iktisat Isletme ve Finans, 22(260), pp. 26–37, 2007.

[70] Y. Yuan, Market–wide attention, trading, and stock returns, Journal of Financial Economics, 116(3), pp. 548–564, 2015.

[71] W. Zhang, S. Lin, and Y. Zhang, Intraday Market–Wide Ups/Downs and Returns, Journal of Management Science and Engineering, 1(1), pp. 28–57, 2016.

APPENDIX A

DESCRIPTIVE STATISTICS

Table A.1: Descriptive Statistics of Cumulative Returns For Event Days ($|0.5\%|$ Filter)

MİNutes	Filter: +0.5%								Filter: -0.5%							
	Nobs	Min	Max	Mean	Median	StDev	SK	KURT	Nobs	Min	Max%	Mean	Median	StDev	SK	KURT
1	749	-0.688	0.792	0.081	0.084	0.165	0.031	2.299	460	-1.402	1.278	-0.068	-0.057	0.229	0.258	7.686
2	749	-0.984	0.847	0.064	0.062	0.214	-0.004	2.193	460	-1.406	1.569	-0.064	-0.070	0.291	0.549	5.054
3	749	-1.379	1.071	0.044	0.050	0.251	-0.238	2.919	460	-1.374	1.785	-0.036	-0.032	0.344	0.471	4.125
4	749	-1.682	1.095	0.026	0.051	0.280	-0.579	3.511	460	-1.613	1.738	-0.015	-0.014	0.381	0.170	3.098
5	749	-1.744	1.055	0.017	0.045	0.304	-0.643	2.782	460	-2.015	2.004	0.011	0.012	0.416	-0.060	4.175
6	749	-1.716	0.967	0.003	0.036	0.328	-0.679	2.135	460	-1.998	1.794	0.034	0.045	0.438	-0.261	3.338
7	749	-1.562	0.965	0.000	0.032	0.344	-0.590	1.735	460	-2.045	1.859	0.061	0.079	0.466	-0.306	3.237
8	749	-1.550	1.073	-0.010	0.021	0.356	-0.613	1.914	460	-2.570	2.145	0.069	0.076	0.482	-0.308	3.724
9	749	-2.027	1.306	-0.017	0.017	0.368	-0.664	2.631	460	-2.709	2.425	0.091	0.117	0.488	-0.216	4.365
10	749	-2.351	1.359	-0.019	0.019	0.379	-0.717	3.231	460	-2.721	2.410	0.101	0.106	0.503	-0.331	4.086
15	749	-3.296	1.748	-0.033	0.020	0.411	-0.966	6.216	460	-2.795	2.220	0.130	0.130	0.517	-0.222	3.376
20	749	-3.565	1.637	-0.036	0.030	0.443	-1.189	6.460	460	-1.765	2.931	0.141	0.128	0.540	0.297	2.409
25	749	-2.506	1.585	-0.042	0.009	0.458	-0.984	3.754	460	-1.835	2.608	0.128	0.120	0.578	0.073	1.792
30	749	-2.006	1.721	-0.046	0.015	0.470	-0.599	2.129	460	-2.492	2.818	0.123	0.121	0.603	0.074	1.994
45	749	-2.766	2.032	-0.073	-0.018	0.536	-0.799	2.876	460	-2.173	2.979	0.164	0.174	0.661	0.214	1.990
60	749	-2.842	2.059	-0.074	-0.024	0.569	-0.816	2.987	460	-2.312	2.657	0.135	0.159	0.683	0.224	1.834
75	749	-3.206	2.819	-0.078	-0.014	0.607	-0.756	3.108	460	-2.752	3.018	0.120	0.145	0.717	0.069	1.945
90	749	-3.090	2.851	-0.079	-0.014	0.640	-0.793	2.912	460	-2.782	2.902	0.114	0.171	0.750	-0.155	1.572
105	749	-3.459	3.431	-0.090	-0.023	0.688	-0.733	3.614	460	-2.715	3.220	0.110	0.155	0.791	-0.236	1.879
120	749	-3.629	2.625	-0.083	-0.012	0.730	-0.784	2.929	460	-3.298	3.438	0.111	0.158	0.851	-0.379	2.312
last60	749	-6.037	6.223	-0.111	-0.046	1.239	-0.628	2.981	460	-7.765	4.764	0.014	0.059	1.489	-0.634	2.754
last30	749	-7.412	6.354	-0.115	-0.052	1.334	-0.701	3.095	460	-5.543	5.282	0.054	0.116	1.561	-0.357	1.397
last15	749	-7.348	5.330	-0.132	-0.042	1.395	-0.785	2.758	460	-5.660	6.008	0.029	0.062	1.620	-0.310	1.477
Close	749	-7.979	5.604	-0.051	0.052	1.465	-0.744	2.771	460	-5.236	6.888	0.170	0.192	1.703	-0.114	1.264

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

Table A.2: Descriptive Statistics of Cumulative Returns For Event Days ($|1\%|$ Filter)

MInutes	Filter: +1%								Filter: -1%							
	Nobs	Min	Max	Mean	Median	StDev	SK	KURT	Nobs	Min	Max%	Mean	Median	StDev	SK	KURT
1	267	-0.688	0.792	0.108	0.095	0.207	0.060	1.479	211	-1.402	1.278	-0.092	-0.072	0.288	0.470	5.897
2	267	-0.984	0.847	0.088	0.077	0.275	0.059	1.102	211	-1.406	1.569	-0.086	-0.102	0.349	0.812	4.727
3	267	-1.379	1.071	0.051	0.045	0.327	-0.110	1.610	211	-1.321	1.785	-0.037	-0.041	0.406	0.744	3.446
4	267	-1.682	1.095	0.014	0.009	0.365	-0.310	1.931	211	-1.452	1.738	-0.018	-0.020	0.445	0.324	2.171
5	267	-1.744	1.055	-0.008	-0.011	0.387	-0.366	1.553	211	-1.839	2.004	0.020	0.008	0.486	0.095	2.968
6	267	-1.716	0.967	-0.039	-0.030	0.411	-0.378	0.906	211	-1.753	1.794	0.045	0.055	0.505	-0.108	2.324
7	267	-1.562	0.965	-0.055	-0.062	0.431	-0.270	0.519	211	-2.045	1.859	0.082	0.081	0.548	-0.198	2.399
8	267	-1.550	1.073	-0.067	-0.064	0.441	-0.345	0.797	211	-2.570	2.145	0.089	0.079	0.562	-0.309	3.288
9	267	-2.027	1.129	-0.081	-0.072	0.450	-0.411	1.493	211	-2.709	2.425	0.108	0.136	0.578	-0.275	4.031
10	267	-2.351	1.359	-0.086	-0.072	0.464	-0.451	2.042	211	-2.721	2.410	0.115	0.139	0.596	-0.454	3.620
15	267	-3.296	1.748	-0.101	-0.107	0.503	-0.793	5.921	211	-2.795	2.220	0.161	0.181	0.604	-0.446	3.267
20	267	-3.565	1.637	-0.106	-0.075	0.548	-1.119	5.995	211	-1.765	2.931	0.185	0.158	0.613	0.290	2.361
25	267	-2.506	1.585	-0.132	-0.096	0.563	-0.746	2.645	211	-1.835	2.608	0.180	0.127	0.653	0.300	1.566
30	267	-2.006	1.721	-0.138	-0.110	0.566	-0.202	1.270	211	-1.576	2.818	0.170	0.130	0.685	0.370	1.239
45	267	-2.766	2.032	-0.163	-0.090	0.638	-0.811	2.319	211	-1.792	2.979	0.266	0.237	0.738	0.421	1.723
60	267	-2.723	2.030	-0.148	-0.114	0.651	-0.745	2.243	211	-2.312	2.657	0.231	0.230	0.763	0.468	1.591
75	267	-3.206	1.849	-0.160	-0.093	0.698	-0.850	2.379	211	-2.071	3.018	0.220	0.209	0.802	0.320	1.416
90	267	-3.090	1.733	-0.156	-0.061	0.726	-0.937	2.315	211	-2.782	2.902	0.209	0.203	0.841	-0.150	1.528
105	267	-3.459	1.980	-0.164	-0.094	0.799	-0.906	2.577	211	-2.715	3.220	0.189	0.211	0.883	-0.160	1.650
120	267	-3.580	2.019	-0.139	-0.050	0.835	-0.819	1.979	211	-3.298	3.438	0.200	0.185	0.936	-0.249	1.892
last60	267	-6.037	6.223	-0.198	-0.070	1.530	-0.591	2.499	211	-6.426	4.764	0.070	0.232	1.643	-0.470	1.346
last30	267	-7.412	6.354	-0.186	-0.071	1.620	-0.708	2.903	211	-5.543	5.282	0.145	0.294	1.737	-0.339	0.763
last15	267	-7.348	5.330	-0.226	-0.069	1.668	-0.831	2.432	211	-5.660	6.008	0.139	0.248	1.814	-0.332	0.838
Close	267	-7.979	5.604	-0.121	0.084	1.766	-0.865	2.406	211	-5.236	6.888	0.308	0.515	1.898	-0.217	0.667

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

Table A.3: Descriptive Statistics of Cumulative Returns For Event Days ($|1.5\%|$ Filter)

MİNutes	Filter: +1.5%								Filter: -1.5%							
	Nobs	Min	Max	Mean	Median	StDev	SK	KURT	Nobs	Min	Max%	Mean	Median	StDev	SK	KURT
1	117	-0.688	0.792	0.110	0.098	0.245	-0.237	0.854	121	-0.848	1.278	-0.094	-0.072	0.320	1.103	4.566
2	117	-0.984	0.822	0.078	0.061	0.327	-0.079	0.400	121	-1.016	1.569	-0.070	-0.093	0.379	1.233	4.219
3	117	-1.379	1.071	0.025	0.023	0.399	-0.173	0.834	121	-1.094	1.785	-0.011	-0.024	0.453	0.942	2.916
4	117	-1.682	0.980	-0.030	-0.057	0.436	-0.288	1.114	121	-1.452	1.738	0.014	0.000	0.480	0.518	1.810
5	117	-1.744	1.055	-0.059	-0.082	0.462	-0.374	0.830	121	-1.839	2.004	0.057	0.011	0.532	0.244	2.568
6	117	-1.716	0.967	-0.101	-0.131	0.494	-0.228	0.128	121	-1.669	1.794	0.084	0.082	0.547	-0.043	1.852
7	117	-1.562	0.965	-0.123	-0.165	0.517	-0.121	-0.168	121	-2.045	1.859	0.140	0.123	0.603	-0.225	2.149
8	117	-1.542	1.073	-0.136	-0.187	0.526	-0.048	-0.082	121	-2.570	2.145	0.163	0.148	0.609	-0.373	3.495
9	117	-1.478	1.129	-0.156	-0.184	0.521	0.026	0.074	121	-2.709	2.425	0.173	0.163	0.620	-0.219	4.474
10	117	-1.436	1.359	-0.167	-0.222	0.526	0.232	0.138	121	-2.721	2.410	0.182	0.203	0.629	-0.378	4.247
15	117	-1.470	1.748	-0.153	-0.216	0.563	0.309	0.440	121	-2.795	2.220	0.229	0.210	0.647	-0.538	3.966
20	117	-1.992	1.637	-0.157	-0.177	0.611	-0.245	0.627	121	-1.377	2.931	0.290	0.254	0.647	0.491	2.280
25	117	-2.506	1.585	-0.174	-0.118	0.671	-0.533	1.324	121	-1.423	2.608	0.308	0.278	0.693	0.489	1.007
30	117	-2.006	1.721	-0.171	-0.128	0.685	-0.058	0.521	121	-1.505	2.818	0.294	0.305	0.751	0.338	0.772
45	117	-2.766	2.032	-0.243	-0.201	0.779	-0.542	1.266	121	-1.639	2.979	0.426	0.440	0.794	0.444	1.510
60	117	-2.723	2.030	-0.242	-0.195	0.774	-0.473	1.299	121	-1.255	2.657	0.374	0.329	0.823	0.679	0.829
75	117	-3.206	1.849	-0.282	-0.209	0.817	-0.663	1.726	121	-1.429	3.018	0.375	0.281	0.843	0.590	0.870
90	117	-3.090	1.733	-0.268	-0.147	0.849	-0.793	1.430	121	-2.519	2.902	0.342	0.279	0.880	0.075	1.036
105	117	-3.459	1.980	-0.309	-0.201	0.952	-0.806	1.738	121	-2.656	3.220	0.323	0.314	0.912	0.064	1.388
120	117	-3.580	2.019	-0.305	-0.188	0.988	-0.660	1.155	121	-2.436	3.438	0.307	0.267	0.949	0.080	1.390
last60	117	-6.037	6.223	-0.382	-0.221	1.850	-0.491	1.854	121	-6.426	4.764	0.134	0.304	1.924	-0.537	0.732
last30	117	-7.412	6.354	-0.347	-0.103	1.979	-0.655	2.142	121	-5.543	5.282	0.184	0.318	2.026	-0.385	0.136
last15	117	-7.348	5.330	-0.425	-0.204	2.007	-0.766	1.673	121	-5.660	6.008	0.190	0.403	2.065	-0.384	0.411
Close	117	-7.979	5.604	-0.283	0.066	2.118	-0.860	1.607	121	-5.236	6.888	0.418	0.666	2.149	-0.277	0.245

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

Table A.4: Descriptive Statistics of Cumulative Returns For Event Days (Second Part)

MInutes	Filter: +0.5% to 1%								Filter: -0.5% to -1%							
	Nobs	Min	Max	Mean	Median	StDev	SK	KURT	Nobs	Min	Max%	Mean	Median	StDev	SK	KURT
1	482	-0.468	0.425	0.066	0.078	0.134	-0.501	1.025	249	-0.730	0.528	-0.048	-0.049	0.160	-0.093	1.076
2	482	-0.670	0.481	0.052	0.060	0.170	-0.523	1.225	249	-0.985	0.880	-0.045	-0.052	0.231	-0.024	1.369
3	482	-0.927	0.641	0.040	0.056	0.198	-0.584	1.939	249	-1.374	0.933	-0.035	-0.025	0.281	-0.305	2.636
4	482	-1.106	0.662	0.032	0.063	0.219	-0.923	2.795	249	-1.613	1.241	-0.011	-0.012	0.317	-0.184	3.456
5	482	-1.070	0.780	0.031	0.066	0.245	-0.849	2.270	249	-2.015	1.338	0.003	0.022	0.348	-0.476	4.914
6	482	-1.204	0.890	0.026	0.065	0.268	-0.822	2.416	249	-1.998	1.285	0.025	0.037	0.374	-0.612	4.095
7	482	-1.154	0.911	0.030	0.055	0.281	-0.708	2.288	249	-1.794	1.298	0.044	0.071	0.384	-0.661	3.004
8	482	-1.371	1.020	0.022	0.048	0.294	-0.641	2.158	249	-1.640	1.528	0.052	0.064	0.402	-0.385	2.348
9	482	-1.504	1.306	0.019	0.049	0.308	-0.653	2.782	249	-1.509	1.433	0.077	0.094	0.397	-0.144	1.390
10	482	-1.711	1.330	0.018	0.059	0.318	-0.722	3.279	249	-1.531	1.636	0.089	0.080	0.408	-0.043	1.738
15	482	-1.603	1.133	0.005	0.048	0.346	-0.814	2.585	249	-1.212	1.814	0.103	0.082	0.429	0.155	1.215
20	482	-1.560	0.968	0.003	0.064	0.367	-0.788	1.784	249	-1.288	1.957	0.104	0.081	0.468	0.123	1.105
25	482	-2.083	1.260	0.007	0.060	0.381	-0.870	2.861	249	-1.764	1.342	0.084	0.087	0.503	-0.530	0.893
30	482	-1.968	1.321	0.006	0.052	0.398	-0.810	2.411	249	-2.492	1.347	0.083	0.111	0.521	-0.667	2.220
45	482	-1.645	1.844	-0.024	0.031	0.462	-0.455	1.705	249	-2.173	1.983	0.077	0.114	0.574	-0.455	0.986
60	482	-2.842	2.059	-0.033	0.003	0.515	-0.739	3.105	249	-2.022	1.658	0.053	0.116	0.597	-0.465	0.822
75	482	-2.408	2.819	-0.032	0.009	0.547	-0.476	2.975	249	-2.752	1.805	0.035	0.111	0.626	-0.638	1.633
90	482	-2.614	2.851	-0.036	0.005	0.583	-0.506	2.741	249	-2.382	1.896	0.033	0.096	0.654	-0.404	0.796
105	482	-3.079	3.431	-0.049	-0.007	0.616	-0.359	3.757	249	-2.670	2.161	0.043	0.137	0.698	-0.532	1.519
120	482	-3.629	2.625	-0.051	0.005	0.663	-0.634	3.334	249	-3.055	2.366	0.036	0.125	0.767	-0.719	2.463
last60	482	-3.874	3.153	-0.062	-0.028	1.042	-0.442	1.079	249	-7.765	4.066	-0.034	-0.010	1.347	-0.911	4.702
last30	482	-4.339	3.234	-0.076	-0.049	1.146	-0.510	1.114	249	-5.346	4.553	-0.022	-0.044	1.394	-0.461	2.082
last15	482	-5.447	3.613	-0.080	-0.040	1.217	-0.540	1.512	249	-5.016	4.811	-0.064	-0.006	1.433	-0.375	2.172
Close	482	-5.770	3.780	-0.013	0.046	1.269	-0.405	1.462	249	-4.800	5.845	0.052	0.096	1.513	-0.072	1.967

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

Table A.5: Descriptive Statistics of Cumulative Returns For Event Days (Second Part)

MİNutes	Filter: +1% to 1.5%								Filter: -1% to -1.5%							
	Nobs	Min	Max	Mean	Median	StDev	SK	KURT	Nobs	Min	Max%	Mean	Median	StDev	SK	KURT
1	150	-0.289	0.726	0.106	0.093	0.172	0.693	1.315	90	-1.402	0.602	-0.089	-0.072	0.241	-1.551	8.299
2	150	-0.652	0.847	0.096	0.085	0.228	0.474	1.187	90	-1.406	0.993	-0.108	-0.109	0.303	-0.473	3.993
3	150	-0.662	0.795	0.072	0.052	0.256	0.446	0.570	90	-1.321	1.012	-0.071	-0.090	0.332	-0.287	2.002
4	150	-1.007	1.095	0.048	0.059	0.295	0.088	1.469	90	-1.449	1.135	-0.062	-0.078	0.391	-0.342	1.876
5	150	-0.958	0.994	0.031	0.019	0.314	0.141	0.805	90	-1.667	1.257	-0.028	-0.013	0.414	-0.565	2.449
6	150	-1.084	0.938	0.010	0.019	0.325	-0.146	0.798	90	-1.753	1.427	-0.008	-0.018	0.439	-0.471	2.709
7	150	-1.061	0.962	-0.002	-0.005	0.343	-0.044	0.483	90	-1.738	1.418	0.003	0.012	0.456	-0.492	1.878
8	150	-1.550	0.976	-0.012	-0.010	0.353	-0.508	1.877	90	-1.746	1.401	-0.010	0.019	0.476	-0.534	1.759
9	150	-2.027	1.068	-0.022	-0.009	0.377	-0.874	4.563	90	-1.789	1.436	0.021	0.058	0.506	-0.669	1.836
10	150	-2.351	0.922	-0.022	-0.003	0.399	-1.325	6.690	90	-1.757	1.383	0.025	0.083	0.540	-0.809	1.676
15	150	-3.296	0.897	-0.062	-0.038	0.448	-2.316	16.358	90	-1.566	1.645	0.070	0.137	0.532	-0.474	0.940
20	150	-3.565	1.016	-0.067	-0.014	0.493	-2.251	15.312	90	-1.765	1.542	0.044	0.032	0.534	-0.509	1.098
25	150	-2.487	0.894	-0.099	-0.089	0.460	-0.898	3.856	90	-1.835	1.203	0.007	0.039	0.554	-0.651	1.236
30	150	-1.849	1.088	-0.112	-0.106	0.454	-0.330	1.137	90	-1.576	1.549	0.002	0.038	0.546	-0.273	0.733
45	150	-2.090	0.982	-0.100	-0.035	0.496	-0.885	1.715	90	-1.792	1.394	0.052	0.095	0.596	-0.341	0.178
60	150	-2.437	1.154	-0.075	-0.036	0.526	-0.848	2.294	90	-2.312	1.297	0.038	0.113	0.629	-0.726	1.207
75	150	-2.077	1.200	-0.065	0.000	0.573	-0.719	1.392	90	-2.071	1.308	0.012	0.091	0.694	-0.685	0.875
90	150	-2.761	1.222	-0.069	-0.031	0.602	-0.762	2.055	90	-2.782	1.445	0.030	0.137	0.755	-0.891	1.731
105	150	-2.275	1.296	-0.052	-0.003	0.636	-0.433	0.842	90	-2.715	1.765	0.010	0.015	0.814	-0.762	1.507
120	150	-2.394	1.650	-0.010	0.048	0.669	-0.495	1.017	90	-3.298	2.027	0.056	0.018	0.903	-0.825	2.167
last60	150	-3.790	2.827	-0.055	-0.018	1.212	-0.286	0.292	90	-3.524	3.298	-0.016	0.116	1.168	-0.212	0.497
last30	150	-3.844	2.914	-0.061	-0.048	1.265	-0.264	0.114	90	-3.870	4.101	0.091	0.243	1.259	-0.131	0.958
last15	150	-4.351	3.299	-0.071	-0.002	1.333	-0.421	0.649	90	-3.995	4.196	0.070	0.127	1.416	-0.199	0.636
Close	150	-5.072	3.858	0.006	0.092	1.426	-0.407	1.072	90	-4.190	4.304	0.162	0.274	1.494	-0.247	0.780

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

Table A.6: Descriptive Statistics of Cumulative Returns For Normal Days

	Nobs	Min	Max	Mean	Median	StDev	SK	KURT
1	2001	-0.708	0.904	0.010	0.018	0.138	-0.166	2.674
2	2001	-0.853	1.022	0.006	0.018	0.176	-0.200	2.318
3	2001	-0.862	1.199	0.005	0.021	0.204	-0.213	2.097
4	2001	-1.155	1.141	0.005	0.026	0.228	-0.387	2.559
5	2001	-1.509	1.225	0.008	0.027	0.246	-0.538	3.748
6	2001	-1.590	1.201	0.009	0.028	0.264	-0.479	3.217
7	2001	-1.662	1.423	0.012	0.029	0.272	-0.407	2.794
8	2001	-1.563	1.475	0.012	0.032	0.282	-0.336	2.833
9	2001	-1.581	1.677	0.014	0.027	0.288	-0.307	2.818
10	2001	-1.842	1.723	0.012	0.026	0.297	-0.308	3.629
15	2001	-1.856	1.733	0.008	0.026	0.331	-0.288	2.573
20	2001	-1.988	1.476	-0.005	0.022	0.356	-0.446	2.503
25	2001	-2.037	1.860	-0.009	0.022	0.372	-0.401	2.634
30	2001	-2.195	1.897	-0.015	0.004	0.386	-0.559	3.133
45	2001	-2.149	2.185	-0.030	0.006	0.434	-0.392	2.178
60	2001	-3.706	2.614	-0.046	-0.007	0.488	-0.620	4.540
75	2001	-4.811	2.639	-0.061	-0.029	0.534	-0.843	6.019
90	2001	-4.568	3.254	-0.073	-0.045	0.568	-0.648	4.736
105	2001	-4.859	3.599	-0.078	-0.052	0.588	-0.620	4.797
120	2001	-3.927	3.651	-0.078	-0.057	0.620	-0.502	3.753
last60	2001	-7.412	4.484	-0.120	-0.087	1.032	-0.322	2.264
last30	2001	-6.773	4.675	-0.138	-0.108	1.101	-0.245	1.704
last15	2001	-6.519	5.072	-0.164	-0.118	1.164	-0.224	1.565
Close	2001	-6.544	5.180	-0.137	-0.101	1.230	-0.153	1.648

Note: Values of minimum, maximum, mean, median and standart deviation are shown as percentages.

APPENDIX B

TESTING FOR NORMALITY AND EQUAL VARIANCES

Table B.1: Shapiro-Wilk[1] and Ansari-Bradley[2] Test Results (First Part)

Minutes	+0.5%		+1%		+1.5%		-0.5%		-1%		-1.5%	
	SW	AB	SW	AB	SW	AB	SW	AB	SW	AB	SW	AB
1	0 *	0 *	0 *	0 *	0.165	0 *	0 *	0 *	0 *	0 *	0 *	0 *
2	0 *	0 *	0 *	0 *	0.182	0 *	0 *	0 *	0 *	0 *	0 *	0 *
3	0 *	0 *	0 *	0 *	0.217	0 *	0 *	0 *	0 *	0 *	0 *	0 *
4	0 *	0 *	0 *	0 *	0.046 †	0 *	0 *	0 *	0 *	0 *	0.001 *	0 *
5	0 *	0 *	0.001 *	0 *	0.073 ‡	0 *	0 *	0 *	0 *	0 *	0 *	0 *
6	0 *	0 *	0.004 *	0 *	0.138	0 *	0 *	0 *	0 *	0 *	0.001 *	0 *
7	0 *	0 *	0.025 †	0 *	0.276	0 *	0 *	0 *	0 *	0 *	0 *	0 *
8	0 *	0 *	0.007 *	0 *	0.392	0 *	0 *	0 *	0 *	0 *	0 *	0 *
9	0 *	0 *	0.001 *	0 *	0.602	0 *	0 *	0 *	0 *	0 *	0 *	0 *
10	0 *	0 *	0 *	0 *	0.286	0 *	0 *	0 *	0 *	0 *	0 *	0 *
15	0 *	0 *	0 *	0 *	0.215	0 *	0 *	0 *	0 *	0 *	0 *	0 *
20	0 *	0.001 *	0 *	0 *	0.218	0 *	0 *	0 *	0 *	0 *	0.001 *	0 *
25	0 *	0 *	0 *	0 *	0.013 †	0 *	0 *	0 *	0 *	0 *	0.011 †	0 *
30	0 *	0 *	0.001 *	0 *	0.178	0 *	0 *	0 *	0.001 *	0 *	0.084 ‡	0 *
45	0 *	0.006 *	0 *	0 *	0.001 *	0 *	0 *	0 *	0 *	0 *	0.002 *	0 *
60	0 *	0.016 †	0 *	0 *	0.004 *	0 *	0 *	0 *	0 *	0 *	0 *	0 *
75	0 *	0.004 *	0 *	0 *	0.001 *	0 *	0 *	0 *	0.001 *	0 *	0.004 *	0 *
90	0 *	0.035 †	0 *	0.005 *	0 *	0.004 *	0 *	0 *	0 *	0 *	0.009 *	0 *
105	0 *	0.01 *	0 *	0 *	0 *	0 *	0 *	0 *	0 *	0 *	0.002 *	0 *
120	0 *	0.005 *	0 *	0 *	0.002 *	0 *	0 *	0 *	0 *	0 *	0.005 *	0 *
last60	0 *	0.002 *	0 *	0 *	0 *	0 *	0 *	0 *	0.002 *	0 *	0.045 †	0 *
last30	0 *	0 *	0 *	0 *	0 *	0 *	0 *	0 *	0.007 *	0 *	0.085 ‡	0 *
last15	0 *	0.001 *	0 *	0 *	0 *	0 *	0 *	0 *	0.009 *	0 *	0.071 ‡	0 *
Close	0 *	0.001 *	0 *	0 *	0 *	0 *	0 *	0 *	0.017 †	0 *	0.098 ‡	0 *

Note: SW : The Shapiro-Wilk Test (Normality Test); AB : The Ansari-Bradley Test (Variance Test).

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level.

[1] Null Hypothesis: Return series of Event Days are normally distributed.

[2] Null Hypothesis: Return series of Event and Normal Days comes from the same distribution.

Table B.2: Shapiro-Wilk[1] and Ansari-Bradley[2] Test Results (Second Part & Normal Days)

Minutes	+0.5% to +1%		+1% to +1.5%		-0.5% to -1%		-1% to -1.5%		Normal[3]
	SW	AB	SW	AB	SW	AB	SW	AB	SW
1	0 *	0.002 *	0.001 *	0 *	0.103	0 *	0 *	0 *	0 *
2	0 *	0.356	0.006 *	0 *	0.035 †	0 *	0 *	0 *	0 *
3	0 *	0.784	0.013 †	0.014 †	0 *	0 *	0.03 †	0 *	0 *
4	0 *	0.841	0.027 †	0 *	0 *	0 *	0.013 †	0 *	0 *
5	0 *	0.911	0.182	0 *	0 *	0 *	0.006 *	0 *	0 *
6	0 *	0.822	0.259	0.003 *	0 *	0 *	0.003 *	0 *	0 *
7	0 *	0.83	0.643	0 *	0 *	0 *	0.019 †	0 *	0 *
8	0 *	0.75	0.009 *	0 *	0 *	0 *	0.024 †	0 *	0 *
9	0 *	0.714	0 *	0.001 *	0.006 *	0 *	0.005 *	0 *	0 *
10	0 *	0.58	0 *	0.001 *	0.001 *	0 *	0.001 *	0 *	0 *
15	0 *	0.742	0 *	0.004 *	0.011 †	0 *	0.039 †	0 *	0 *
20	0 *	0.788	0 *	0.015 †	0.028 †	0 *	0.062 ‡	0.001 *	0 *
25	0 *	0.617	0 *	0.001 *	0.001 *	0 *	0.006 *	0.013 †	0 *
30	0 *	0.572	0.077 ‡	0.005 *	0 *	0 *	0.135	0.007 *	0 *
45	0 *	0.518	0 *	0.143	0.006 *	0 *	0.346	0.002 *	0 *
60	0 *	0.804	0 *	0.052 ‡	0.003 *	0 *	0.026 †	0 *	0 *
75	0 *	0.317	0.001 *	0.134	0 *	0 *	0.005 *	0.001 *	0 *
90	0 *	0.455	0.001 *	0.18	0.022 †	0 *	0.001 *	0.001 *	0 *
105	0 *	0.609	0.041 †	0.02 †	0 *	0 *	0.001 *	0.01 *	0 *
120	0 *	0.703	0.021 †	0.02 †	0 *	0 *	0.001 *	0.008 *	0 *
last60	0 *	0.624	0.254	0.011 †	0 *	0.007 *	0.568	0.098 ‡	0 *
last30	0 *	0.298	0.517	0.011 †	0 *	0.009 *	0.243	0.105	0 *
last15	0 *	0.446	0.072 ‡	0.019 †	0 *	0.05 †	0.366	0.021 †	0 *
Close	0 *	0.545	0.015 †	0.004 *	0 *	0.02 †	0.229	0.015 †	0 *

Note: SW : The Shapiro-Wilk Test (Normality Test); AB : The Ansari-Bradley Test (Variance Test).

Significance Level: * Significant at the 0.01 level ; † Significant at the 0.05 level ; ‡ Significant at the 0.10 level.

[1] Null Hypothesis: Return series of Event Days are normally distributed.

[2] Null Hypothesis: Return series of Event and Normal Days have same distribution.

[3] Null Hypothesis: Return series of Normal Days are normally distributed.

APPENDIX C

NON-PARAMETRIC TESTS

The Wilcoxon signed-rank test :

After calculating differences between pairs, we rank the values with regard to their absolute values of differences and sum of the positive and negative ranks are computed. The minimum of these values determine the test statistic W.
In case of large number of observations, we follow the following procedure; We use minimum W for the test statistic, then, mean of the W distribution is calculated by:

$$\mu = \frac{n(n+1)}{4}$$

where n represents the sample size.
The standard deviation of the W distribution is

$$\sigma = \sqrt{\frac{n(n+1)(2n+1)}{24}}$$

To compute the z-value, the formula is

$$z = (W - \mu)/_{\sigma}$$

The Mann-Whitney U test :

To define U values of samples, the following formula is used:

$$U_1 = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1,$$

$$U_2 = n_2 n_1 + \frac{n_2(n_2+1)}{2} - R_2,$$

$$U = min(U_1, U_2)$$

where n represents the sample size and R represents the adjusted rank-sum for the samples.
In case of large number of observations, we can use the following procedure;
The mean of the distribution of U values is calculated by:

$$\mu = 0.5 \times N1 \times N2$$

where N_1 denotes the number of participants in condition 1, and N_2 denotes the number of participants in condition 2.

To compute the standard deviation of U values, the formula is

$$\sigma = \frac{(N1 \times N2) \times (N+1)}{12}$$

note that N denotes the total number of participants.

In case of having ties, total sum of the ties is measured by:

$$T_c = \sum (t^3 - t)$$

where t denotes the number of ties for each tied value. Then, standard deviation is calculated by:

$$\sigma = \sqrt{\frac{(N1 \times N2) \times (N^3 - N - T_c)}{12N \times (N-1)}}$$

Finally, critical value of U is calculated by:

$$U = \mu - z \times \sigma - 0.5$$

APPENDIX D

EXCLUDED DATES

Table D.1: Excluded Dates

Year	Date
2007	2007-05-01 / 2007-05-02 / 2007-07-02 / 2007-07-03 / 2007-07-12 / 2007-07-13 / 2007-10-11 / 2007-11-28 / 2007-11-29 / 2007-12-19
2008	2008-09-29 / 2008-10-28 / 2008-11-24 / 2008-11-25
2009	2009-10-28 / 2009-11-24 / 2009-11-25 / 2009-11-26
2010	-
2011	2011-10-28
2012	2012-03-02 / 2012-10-24
2013	2013-06-10 / 2013-06-11 / 2013-08-07 / 2013-10-14 / 2013-10-28 / 2013-11-15
2014	2014-07-23 / 2014-10-03 / 2014-10-28
2015	2015-07-16 / 2015-09-23 / 2015-10-28
2016	2016-07-04 / 2016-10-28
2017	2017-08-31
2018	2018-06-14 / 2018-08-20
2019	2019-06-03
2020	-