Istanbul Bilgi University Institute of Social Sciences
Department of Financial Economics

Google Trends Search Volume Index in Estimation of Istanbul Stock Market Index (BIST)

Google Trends Arama Hacim Endeksinin Borsa Istanbul Endeksi (BİST) Üstünde Testi

M. Emre BİLGİÇ

Istanbul Jan 2017

Google Trends Search Volume Index in Estimation of Istanbul Stock Market Index (BIST)

Google Trends Arama Hacim Endeksinin Borsa Istanbul Endeksi (BİST) Üstünde Testi

Submitted by

M. Emre BİLGİÇ

115620017

Asst. Prof. Serda Selin Öztürk ______________________
(Dissertation Advisor)

Asst. Prof. Haluk Yener ______________________

Asst. Prof. Ender Demir ______________________

Anahtar Kelimeler:
1. Borsa veri tahmini
2. Google arama hacimleri
3. Web aramaları ile talep tahmini
4. Borsa işlem hacmi tahmini
5. Borsa İstanbul

Keywords:
1. Stock market estimation
2. Google web search data
3. Demand estimation with web data
4. Stock market transaction volume
5. Istanbul Stock Exchange Market

Abstract

Internet became a considerable part of our lives so fast that even for the ones who lived most of their lives without the internet cannot imagine how the life would be without it. We shop, plan, talk to friends/family, search for information via the internet and doing that we create a movement (trace) that reflects our interests even when we use it anonymously.

The stock market estimation with internet data is a subject that creates motive in researchers to observe if the sentiment or interests of the people affect stock markets and if that effect creates a prediction possibility. Regarding Turkey financials, two works prepared with the internet data. First one is Öztürk & Çiftçi (2014) [25] that analyzed the Twitter sentiment index and tested the USDTRY exchange rate with past index values and found a significant relationship. The second is Gündüz & Çataltepe (2015) [26] that analyzed the financial magazine sentiment data and tested the past data significance on Istanbul Stock Market Index (BIST) the result of which was a significant explanatory power of the sentiment existed.

This study is prepared with daily [Jan.2015-Oct.2016] GTSV volume data of BIST related keywords and focuses on whether if change in the Google Trends Search Volume Index has any significant effect on Istanbul Stock Market Index (BIST) volume data and absolute return. The search volume of keywords found significant in the estimation of transaction volume and absolute return.

Özet

İnternet hayatımızın önemli etkenlerinden biri haline geldi, öyle ki hayatının önemli kısmı boyunca telefon ve internetten uzak olan kişiler için bile internetin yokluğu düşünülemez hale geldi. Bunun sebebi temel olarak internetin yoğun ve çok geniş bir bilgi kaynağı olmakla birlikte kolay erişilebilir olmasıdır. Herhangi bir bilgiye erişim gerektiğinde artık ilk iş olarak tanıdığımız birine sormak yerine arama motoruna yazmamız yeterli oluyor. Ek olarak internetin sağladığı eğlence (müzik dinleme, film izleme, online oyun platformları gibi) ve iletişim olanakları (Facebook, Twitter, Skype, Whatsapp gibi iletişim platformları) da gün geçtikçe daha çok insanın internet kullanıcısı olmasını sağlıyor.

İnternetin sağladığı olanaklar insanların ilgisini cezbederken kullanıcı sayısı da gün geçtikçe artmaktadır. Eğer bu artış bir kullanıcı sayısı grafiği ile gösterilseydi günümüzde bu sayının artış hızının dahi arttığı (ivmeli artış) gözlenebilirdi. Bu durum, bir yandan dünyayı hızlı değiştiren her gelişme gibi teknoloji ve sosyal yaşamımızın nasıl değiştiğini gözlemleme fırsatı sunuyor bizlere, diğer bir yandan aklımızdan geçenleri sorduğumuz internet platformunda düşüncelerimizin tüm dış dünya tarafından gözlemlenebilir olmasına imkan sağlıyor. Yazdıklarımız, düşündüklerimizi ifade ediş şeklimiz veya aradığımız bir şey hareketlerimizin tahmin edilebilmesi ihtimalini de beraberinde getiriyor. Bu konularda çeşitli platform verileri ile yapılan çalışmalarda geçmiş internet verileri esas alınarak yapılan tahminlerde başarılı sonuçlara ulaşılmıştır. Finans piyasaları üzerine de çok sayıda çalışma yapılmış ve etkileşimin bulunduğu doğrulanmıştır. Borsa İstanbul özelinde Gündüz ve Çataltepe (2015) tarafından yeni yapılan bir çalışma Türkiye finansal basın makalelerinin borsa üzerindeki etkisini doğruladı. Öztürk ve Çiftçi (2014)[25] tarafından yapılan bir çalışmada da USD-TRY kuru değişiminin geçmiş Twitter mesaj verileri sentimenti ile anlamlı bir ilişkisi olduğunu ortaya çıkardı.

Burada anlatılacak çalışma dünyanın arama motoru pazarını baskılayan Google arama motorunun Borsa İstanbul'u işaret eden anahtar kelimelerin arama hacimleri verilerini kullanarak Borsa İstanbul'a (BİST) talebi ölçmek ve bu ölçümün borsa işlem hacmi tahmininde ne derece anlamlı sonuçlar verdiğini test etmektir. Mevcut olarak Borsa İstanbul özelinde Google arama hacim endeksi kullanılarak yapılmış bir çalışma olmadığı için, literatüre de katkı sağlayacağını umuyorum. 2015-2016 yılları verileri kullanılarak, 458 günlük veri ile yapılan regresyon çalışması sonucu t-2'ye kadarki arama hacim değişikliklerinin borsa hacim değişikliği üzerinde anlamlı tahmin ($p<0.01$) niteliğinin

bulunduğu gözlemlenmiştir. Benzer ilişkinin mutlak endeks getirisinde de bulunduğu doğrulanmıştır.

Contents

1. Introduction

Through the history of humanity, some developments changed the world abruptly and provided the people the opportunity to observe how the world was changing. Invention of wheel, invention of powdered guns, discovery of America, motor vehicles, air transport, invention of computer are examples of those milestones. The most recent development of this kind is the invention of internet, considering it puts its mark on the beginning of the 21st century.

Internet became a considerable part of our lives so fast that even for the ones who lived most of their lives cannot imagine how the life would be without it. We shop, plan, talk to friends/family, search for information via internet and doing that we create a movement (trace) that reflects our interests even when we use it anonymously.

Internet is a valuable information source that can give idea on what people think and interested in. Which allows the demand estimations to get more precise as Choi & Varian [15] presents. Internet is a deep sea that include irrelevant information or disinformation as well as relevant. Therefore, to avoid the manipulative data, one must be working on the data of the platforms that is widely preferred. Yahoo! Finance, Google, Twitter, Facebook, famous magazine websites are examples among many.

The matter of estimation is limited with the imagination of the researchers. One of the top subjects on estimation side is, as being directly about money, stock market estimation. Efficient Market Hypothesis (EMH) [27], which is the most popular theory in the stock markets literature, states that markets include all the publicly available information in prices and so it is not possible to predict the tomorrow's market moves with today's data. Through time, there were many supports and critics existed on EMH. Considering the available data in internet that allows measuring the sentiment and the interests of public, there have been researches that showed that there are some significant predictors.

The researches that found significant relations categorized by their data sources. Some researchers used one source and some used combinations of sources. Wysocki (1998) [34] only used Yahoo Messaging Boards' data which was available then but still found significant results.

The most famous source among the researchers was Twitter that is an online news and social networking platform that has a character limitation of 140. Twits are reflecting the public sentiment and previous day sentiments might have a reflection in stock markets. Researchers noticed that Twitter is a widespread and famous platform and decided to analyse the twits either analysing message content with text mining techniques or just counting the related message volume. Tayal et al. (2009) [31], Vincent & Armstrong, M. (2010) [33], Bollen et al. (2011) [5], Sprenger & Welpe, I. M. (2010) [30], Zhang et al. (2011) [35], Rao & Srivastava (2013) [27] and Öztürk & Çiftçi (2014) [24] are the researches that took only Twitter data as the source. At Bar-Haim (2011) [3], researchers worked with Stocktwits platform data and found significant estimation results.

With the development of high-level text mining techniques, the finance newspapers and magazines became available to be as predictor data sources. The main idea behind was the expert opinions that might be directing the investors with recommendations. That might be observed by analysing the contents of the articles and creating an expert sentiment. The researchers analysed past news data had significant results at estimation of stock markets. Chowdhury et al. (2014) [9], Ishima et al. (2014) [16], Joshi et al. (2015) [17], Gündüz & Çataltepe (2015) [15] are the studies used news.

Google Search Engine is dominating the search engine market with 77.82% share [38]. Google is providing Google Trends Search Volume Index as a free public service that means it is possible to observe what people are interested in or how their interest has changed in time. This observation is possible on stock markets as well and various researchers worked with Google Trends data. Mao et al. (2011) [23], Preis et al. (2013) [26] and Beer et al. (2013) [4] are the main studies that had successful results with the data.

There are some researchers worked with combinations of data sources. Antweiler & Frank (2004) [1] and Gu et al. (2006) [14] gained successful results by working with Yahoo! Finance and stock market specific websites data. Ruiz et al. (2012) [28] gained the significant relationship using Google and Twitter data. Levenberg et al. (2013) [19] had significant results using extensive web sources including Yahoo, Google, Twitter and web news sources. In research, Loughlin et al. (2013) [20], stock market specific platforms and Google Search data were used resulting in significant results.

There were two available studies, namely Gündüz & Çataltepe (2015) [26] and Öztürk & Çiftçi (2014) [25], made on Turkey economy indicators (BIST and USDTRY) but none was by using Google Trends Search Volume Index data. Öztürk & Çiftçi (2014) [25] was related to USDTRY and completed by using Twitter data. Gündüz & Çataltepe (2015) [26] was a research on predicting the BIST with the finance magazines text mining.

The motives in the study presented here are various. First, the curiosity of how the findings changed in time with the improvement of the number of internet users. As quality of the internet data is dependent on the number of people that use it while the internet usage spreads, the results of estimation model might evolve to another way. For example, the relation that was significant once, in time might be insignificant or vice versa. The second motive is to observe how the available internet sources estimate Istanbul Stock Exchange Market (BIST).

The third one is to understand the meaning of Google Trends Search Volume Index (GTSVI) properly. As GTSVI provides the interest to a keyword, the volume index change of that keyword must be showing the change in demand of the real world value that keyword presents. As I choose the keywords related to Istanbul Stock Index, the changes should indicate a change connected to keyword volume changes. The 4th and last aim is to test the GTSV on BIST as there was no such study in the literature.

My study is prepared by using Google Trends Search Volume Index (GTSVI) of 458 days between Jan-2015 and Oct-2016 as the data source to test whether if the changes in some keywords' search volume index is meaningful in estimation of Istanbul Stock Exchange (BIST). To my knowledge, this is the first study using GTSVI for the estimation of BIST indicators. My test results showed change in keywords search volume at lag 1 and 2 is significant in estimation of BIST index's absolute return and change in transaction volume.

The next section is a review of past works that used the internet data to predict. Works to be told are chosen mainly among the works that worked on estimation of stock market parameters but there are some works that used internet data for estimation of useful real world data. 3rd section first tells about Google Trends platform, then how the data was chosen and collected. The last part of 3rd section summarizes the GARCH model and defines the model I use in this study. 4th section gives the estimation results. Finally, I conclude in section 5.

2. A Review of Past Works

Efficient Market Hypothesis(EMH), which is the most popular theory in the stock markets literature is presented by Fama (1970) [13], says that there is no way to predict the market as markets adjust to all the relevant information faster than any investor. There were supporters of the Efficient Market Theory in many ways and one of them was ‘A Random Walk Down Wall Street’ by Malkiel (1973) [21] which stated that markets follow a random walk and a portfolio that was created by picking random stocks could succeed as much as stock market professionals.

There were critics about the EMH from behavioural economics side. DeBondt and Thaler (1995) [10] underlined the effects of optimism and pessimism of investors created a systematic deviation from the actual state of the markets. They also indicated that their statement was consistent with Kahneman and Tversky (1982) [18] in the way that investors were systematically overconfident on their forecasts and this could lead the diversion. Another behavioralist Shiller (2000) [29] stated the United States stock market upward trend towards the end of 1990s was related to psychological state of that time in United States. His point was that investors were affected from the prosperity during that time leading to market rise irrationally. There observed a tendency on investors to underreact the new information.

The main past works related to useful real world data estimation via social media and web data are provided in this section below. It is required to state that most of the articles summarized below are the analysis results of financial market focused researches. For the categorization of the related literature table 2.1 below can be viewed.

Literature Reference	Methods			Sources					Significant?
	volume	text mining	experts	yahoo	Google	twitter	newspapers	stock blogs	
1	1			1					Yes
2		1						1	No
3	1			1					No
4	1							1	No
5	1			1				1	Yes
6			1	1				1	Yes
7		1				1			Yes
8		1	1			1			Yes
9		1				1			Yes
10	1	1				1			Yes
11	1				1				Yes
12		1				1			Yes
13		1				1			Yes
14			1					1	Yes
15		1			1				Yes
16		1			1	1			Yes
17		1				1			Yes
18		1		1	1	1	1	1	Yes
19	1				1			1	Yes
20	1				1				Yes
21	1				1				Yes
22		1					1		Yes
23		1					1		Yes
24		1					1		Yes
25		1				1			Yes
26		1					1		Yes

Table 2.1. The literature references, used methods and the data sources provided in the table.

The enthusiasm about the subject starts with Wysocki (1998) [34] who made a research regarding the message volume of 3000 stocks in Yahoo! Message boards and noticed that overnight message posting volumes was able to predict the market trade volume and returns. On the regression that he formed with 50 firms (having the highest message volume in Yahoo! Finance) and 6 months' daily data. lag 1 message volume data over the past 5 days moving average was significant with p=0.013 when predicting lag 1 number of shares that changed hands volume data over the past 5 days moving average. In the same way they were able to predict absolute abnormal return of the stocks significantly with p = 0,0023.

Dewally (2000) [11] aimed to explain the value of the investment advice provided from the several stock recommendation websites. His explanatory variable was the positive, negative and neutral message counts in the web sites and dependant variable was the stock returns of selected stocks in NYSE, NASDAQ, OTC BB and Canadian exchange. He did not find any significant effect of news or messages on the stock return and also he noticed the momentum trading behaviour. However, his work was even before the Twitter founded and Google trends data to be public. Tumarkin & Whitelaw (2001) [32] made a study with the daily message volume data in ragingbull.com. Their finding was, unlike Wysocki (1998) [34], that message volume was neither meaningful for the next day's trading volume nor there could be made an estimation for the return via the message volume. However, they concluded that relationship was vice versa, that is the internet data is affected from the volume and return of stock market.

Bommel (2003) [7] contributed the literature with his working paper by underlining rumourmongers and uninformed traders relationship. Finally, it is noted that the rumours seemed having volatile but observable effects in the stock markets.

Antweiler & Frank [1] are one of the firsts of the literature with their published work in 2004. Even as of 2004 not much of the investors were reflecting their actions in internet nor the followers of the stock market message boards, they were able to observe the relation of message volume with Volatility Index. The data they worked on predicting belonged to 45 big company including Intel, Microsoft, and P&G. The message volume data collected from Yahoo Finance and Raging Bull websites. As a result, they noticed a positive correlation between message volume and Volatility Index. Their effect on stock returns noted as statistically significant but economically small.

Gu et al. [14] made their analysis on 2005-2006 Yahoo! Finance data and used the same 45 Dow Jones stock data that Antweiler & Frank [1] used. Differently from them, Gu et al. took the message content into account by recommendation categories available in the website (1-day-holding, 1-week-holding and 1-month holding) as separate explanatory variable and tested the categories according to their date recommendations. Moreover, they rated the users and added more weight to the successful prediction owner messages. As of their regression, coefficients of the messages were significant in lag 1, lag 2 and lag 3 which indicated that the prices might not reflect the message board information at the time they were typed as efficient market theory claims.

Tayal et al. (2009) [31] prepared their research with the stock recommendation blogs and Twitter 2008-2009 data of Microsoft and Google stocks. They built a sentiment index from the posts and created a prediction system using the index as input. The message contents were systematically rated [-5,5] by focusing on the adjectives that were categorized according to their negativity and positivity strengths. Comparison of their prediction with real data indicated a good correlation between predicted results and real data. Even though the results were changing stock or blog size wise, the minimum correlation result was above 0.766.

Vincent and Armstrong [33] worked on Forex data to see if using the Twitter alert would be increasing the FX profit significantly. Twitter alert was the output of algorithm they developed that gives alert according to the new words written by the sample Twitter user pool chosen by them. New words were defined as not existing in the library that was automatically created by analysing the sample users' past twits. As a result, 5 months run, they observed that the buy and sell strategy that they built via Twitter data improved profits 0.56% to 1.27% per month.

Bollen et al. (2010) [6] created a model that measures the Twitter Sentiment with the help of Google Profile of Mood States(GPOMS) tool that categorizes the mood of the text in 6 categories. Estimation data gathered from the twitter posts related to the stock market for the

10 months' data in 2008. The result of the regression of past 7 days Twitter moods data on Dow Jones Index returns was found meaningful at the coefficients of Calm (lag 2...lag 6) and Happy(lag 6) mood states.

Sprenger and Welpe (2010) [30] worked on explaining twitter sentiment data, stock return data and message volume-trading volume or volatility relationship. One of their findings was that the users that had proven good advice history to be retweeted more than the others had. With the extensive work they created, most of the findings related to positive association of contemporaneous message volume data with volatility, higher returns and trading volume. In addition, they detected a lagged relationship exists in message volume and trade volume.

Mao et al. (2011) [23] analysed both Google Trends Search Volumes (GTSV) and news sentiment to predict the Dow Jones Index in 2010-2011 data. They tested weekly search volume data, found a significant estimation capability on trade volume, volatility, and return in Dow Jones by also verifying the relation with Granger's Causality Test. However, they did not have a chance to test GTSV daily data, as Google was not providing that service at the time they prepared their work.

Asur & Huberman (2011) [2] analysed 2.89M Twitter messages related to a list of movies whose release dates are between the dates 13-11-2009 and 26-02-2011. Categorizing the messages according to their sentiments namely Positive, Negative and Neutral created a linear regression model to predict the movies' revenue. The result of their work was to prove the existence of a strong relationship between revenues and related twitter data. Their work was one of the important works on the subject on how to utilise social media data and neatly proven that how digital data is helpful for the estimations of when used properly.

The work of Zhang et al. (2011) [35] was again on Twitter data. They worked on 6 months' data and checked the relation of data with NASDAQ, S&P500 and Dow Jones. They collected the data according to the emotion tags of messages like negative, positive, hopeful, happy, worried etc. and checked the correlations of the data with t+1 index movements and volatility index. What they found was negative (anxious, worried and negative) post counts have a stable ($p<0.01$) negative correlation with the return data and positive correlation with volatility data. Counts of 'Hope' found significantly and negative correlated with return data but the result expected as positively correlated.

Bar-Haim et al. (2011) [3] worked on microblogs message data. Like Gu et al. [6], they focused on expertize of the message posters. They rated the users and found the experts with the algorithm they built. Detecting the experts and focusing expert messages data, they observed enhancement in their stock price movement estimation.

Choi & Varian's (2011) [8] made analysis with Google Trends data. Their study was not directly related to stock markets but was aiming to show Google Trends data is useful for estimation. The estimations were on; sales volume (US with lag 1 and lag 12 trends data), unemployment (US was accepted as random walk and no estimation was successful), travel amount (Several countries like US, JP, FR, IT etc. with R^2 average of 73.3%), consumer confidence (Australia Roy Morgan Consumer Confidence Index lag 1 trends data was highly meaningful). The research results are important for showing the strength of web data in estimation of important factors in economy management.

Rao & Srivastava (2010) [27] also worked on 15 months Google Trends Search Volume and Twitter data together in 2010. The dependent variables were DJIA, NASDAQ and commodity prices (gold and oil) have tested the estimation results with the sentiment predictors. The result of their test was a success, which they found model with sentiment predictors found superior in predicting the indexes compared to the estimation model without sentiment predictors.

Ruiz et al. (2012) [28] worked on 150 chosen stocks' first 6 months' data of 2010 from Twitter posts that included the stock code or the name of the company and dollar sign ($) or a hashtag (#) with it. Decreasing the list of stocks to 20 (20 biggest companies) checked the correlations of the data with the return and trade volume data that was obtained from Yahoo! Finance web site and detected significant results with past Twitter data. Furthermore, they tested the Twitter-based strategy against the random strategy and observed that the Twitter strategy was superior.

Levenberg et al. (2013) [19] made a wider analysis with not only the Twitter or Google Trends Data but whole news database of 700 news sources from 2000 to 2012. They analysed the economy and employment related text in the websites sentence-by-sentence (6.6 M sentences) via the machine-learning framework they formed. Their focus was on predicting Non-Farm Index (NFI) as it was a solid indicator of where the markets head. They used Independent Bayesian Classifier Combination (IBCC) model to test combinations of the sources sentiment indexes on NFI prediction and, as a result, observed 0.85 prediction accuracy.

Loughlin and Harnish (2013) [20] tested Stocktwits.com Twits volume and Google Trends search volume data for 4 stocks (Facebook, Microsoft, Apple, Google) and checking whether the volume data of each is lagging or leading predictors by checking the betas. Their finding was Stocktwits data was able to predict the stock return but Google Trends data was not.

Preis et.al.(2013) [26] analysed the Google Trends search volume data and analysed performance of 98 search terms related to stock markets. Their work was testing the Trends based investment strategy in Dow Jones by using publicly available search volume index of

Google Trends on weekly basis between 2004 and 2011. The result was better than the random strategy with the final profit of 326% (compared to random strategy whose result was 30%).

F. Beer et al. (2013) [21] created an investor sentiment index from Google search volume of the words under categories “economy” and “negative” in General Inquirer Harvard IV-4 dictionary and tested its significance in VAR analysis with mutual funds and stock market in France. The result of their work was that investor sentiment had a negative coefficient and a meaningful p value in 2 weeks’ data set; however, the coefficient turns to positive over the next 3 to 4 weeks. Their work also suggested that the small firms’ values related more with the trends data than the large ones.

Chowdhury (2014) [9] worked on creating a prediction model on Stock trends of the 15 worldwide companies (like IBM, Google, Apple etc.) stocks. The model built on the news sentiment index, which created by analysing 4 weeks’ interval news about the companies and categorizing the news as positive, neutral and negative. The model was accurate 70% of given time. However, it needs to be underlined that the model was working with present data and presented as a support for Efficient Market Hypothesis.

Ishima et al.’s (2014) [16] work was related to the Nikkei and Nikkei Finance Magazine relationship. The magazine articles were analysed for 2007-2012 interval according to an index created as function of negative and positive words in the articles. The result was that the sentiment index was meaningful at third lag.

Joshi et al. (2015) [17] recently made a study on predicting stock trends via news sentiment. They used a classification model as Chowdhury (2014) did and categorized the messages according to the sentiment but with a difference they only used positive and negative as categories. Their work had detailed analysis of which sentiment classification is better in detecting the sentiment (among SVM, Random Forest, Naïve Bayes RF provided best results) They only focused on Apple Inc. stock returns between 2013-2016. In their article they concluded that it is possible to predict the stock trend looking at the past news history from 88% to 92%.

Öztürk & Çiftçi (2014) [24] made their research on Twitter data of [01-2013, 12-2013]. By analysing the Twits that include 'USDTRY', they categorized the posts as negative, positive and neutral. They used LOGIT model to test the significance of lag 1 counts of all three categories. They found a significant relationship with negative and positive lag 1 counts on the exchange rate USDTRY. They also observed that neutral twits did not have any relation.

Gündüz et al. (2015) [15] had a research on BIST 100 index estimation by using Public Disclosure Platform of BIST and financial newspapers. Their result was again a success in estimation of whether the market will be up or down. They predicted the market up and downs correctly 74% of the time.

The research told in sections below is prepared using 2015-2016 Google Trends Search Volume Index(GTSVI) of keywords that are selected to indicate the interest in Istanbul Stock Market Index BIST. The objective is to test the significance of GTSVI on the absolute return and the transaction volume of BIST.

3. Methodology

Time series data has a property of having autocorrelation between subsequent residuals. As I decided to analyse financial data I chose the regression method that is approved with the data. Since the literature suggests that volatility should be taken into consideration while working with stock market data to use GARCH (Generalized Autoregressive Conditional

Heteroscedasticity) model for testing the relationships. However, we do not concentrate on the significance of volatility parameters we only test the significance of coefficients of search volume of keywords. The method and variables will be texplaıned at part 3.3.

3.1. About Google Trends Data

Google Trends is a facility of Google that is open to public. Trends is a platform that provides the search volume graph and data of given keyword starting from 2004 or any year after that to whatever year to be chosen. Trends search can be differentiated by categories (like finance, automotive, entertainment etc.), country, cities and at some countries in district level.

Trends platform enables comparing the search words trends history in graphs so that user could understand how the keyword performed compared to the reference keyword. Figure 3.2.1 provides an example of a keyword history comparison. The graph taken from Google Trends website show how 'imkb' keyword search volume decreased compared to keyword 'hisse' (that is a Turkish word means share and mostly used for stock). Furthermore, how in 2013 it was started to be replaced with 'bist', when IMKB (ex-short name of Istanbul stock exchange market) changed to BIST (Borsa Istanbul).

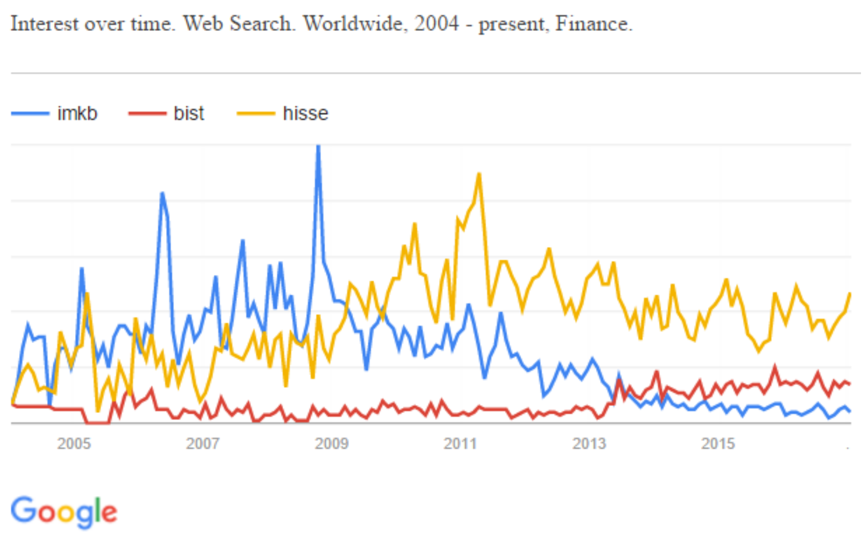

Figure 3.1.1 Google Trends Search Volume Index historical search volume graph of keywords.

The search mechanism works with some rules and query results include only the phrase given. For example, above searches were the graphs of search queries that include the given keywords. However, ‘bist’ and ‘borsa istanbul’ serve the same purpose and for providing the combination of words and/or functions were enabled in the search queries. In Figure 3.2.2 it could be observed when the or condition added to ‘bist’ volume data.

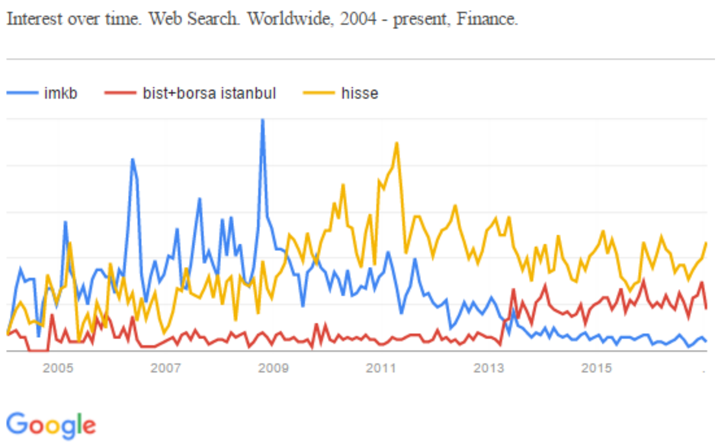

Figure 3.1.2 Google Trends Search Volume Index historical search volume graph of keywords. To observe the difference of ‘+’ sign.

Google Trends daily data comes with a slight challenge that is; the daily data can be downloaded only with at most 3 months’ length at a time and each file indexed according to highest volume which is accepted as 100. Remaining days’ volume data is given relative values. Google trends weekly data is available without time limitation and so provides whole data in weekly scale which provides the chance to know each week’s volume relative to highest week. Thus, assuming to be worked with 1-month scale daily data, the data must be normalized according to weekly data for a useful analysis. The reason behind is the relativity of the highest search volume data. (One month’s highest can even be the other month’s lowest)

The normalization of the data is formulized as below:

RDV_{wi}: Volume index of i'th day of week w that is indexed relative to the month's highest volume.

$RWV_{w:}$ Sums of RDV_{wi} for week w.

where i ={1,2,3,4,5,6,7}

WV_w: Volume index of week taken from Trends.

DV_t: Indexed Volume of t^{th} day relative to highest week search volume in the history of the data.

$$RWV_w = \sum_{i=1}^{7} RDV_{wi} \qquad \text{Equation 3.1.1}$$

$$DV_t = \frac{WV_w}{RWV_w} x RDV_{wi} \qquad \text{Equation 3.1.2}$$

Note: For each w and i couple there is a t.

There is also a service in Google Trends that allows users to see what are the main searches with the queried keyword. As an example the query result for keyword 'hisse' is provided below in Figure 3.1.2. This is helpful because a word could mean different things in different languages like 'ISCTR' is stock code of Is Bank ant at the same time a government department in Romania (ISCTR: Inspectoratul de Stat pentru Controlul in Transportul Rutier). This interface allows to understand the content of the search volume of keyword.

hisse net forum	Breakout
hisse net	+2,250%
bigpara	+1,350%
bigpara hisse	+1,350%
mynet hisse	+1,350%
akbank hisse	+700%
hisse yorumları	+700%
hisse forum	+300%
hisse yorum	+200%

Figure 3.1.2 Google Trends Search Volume Index the main searches list that include the keyword

3.2. Data collection process

As I will check the significance of past trends data with GARCH I need data to be stationary. Therefore, I work with log changes of all dependent and explanatory variables.

The data collection started by choosing which dependent variable to use and what method to test the relation. The time scale of the data was an important factor to choose. As I would be making the analysis for Turkey and because of the political instability even hourly basis, I found it proper to work with daily data instead of monthly or weekly.

Google Trends provides the search volume of the given keyword. The aim in this study is to test whether past daily trends data provides any estimation regarding stock market parameters. It could help predicting transaction volume. Furthermore, as volume estimation might not indicate if the return changes or not I also tested absolute return data.

Taking the decisions, I formulated the dependent variables as follows:

t: indicates the order of day.
I_t: Stock market index value of the t^{th} day.
R_t: Logarithmic return value of the t^{th} day stock market index.
AR_t: Absolute value of R_t.
V_t: Transaction volume of the stock market index at day t.
VC_t: Transaction volume logarithmic change at day t.

$$R_t = \ln\left(\frac{I_t}{I_{t-1}}\right) \qquad \text{Equation 3.2.1}$$

$$AR_t = \left|\ln\left(\frac{I_t}{I_{t-1}}\right)\right| \qquad \text{Equation 3.2.2}$$

$VC_t = \ln(\frac{V_t}{V_{t-1}})$ Equation 3.2.3

To test the significance of any data on Istanbul Stock Market, assuming any of the indexes among BIST, BIST 100 or BIST 30 would be proper, I decided to go on with daily BIST 100 data (includes 100 biggest firm stocks in stock market) that is available free of charge in investing.com website [37]. The descriptive statistics of the dependent variables are given below in the Table 3.3.1.

Sample 1 458 Observations 458		
	VC_t	AR_t
Mean	-0.000691	0.010371
Median	-0.006632	0.008588
Maximum	1.193890	0.073480
Minimum	-1.099565	2.37e-05
Std. Dev.	0.256340	0.009177
Skewness	0.481434	1.982828
Kurtosis	8.427145	9.845780
Jarque-Bera	579.7711	1194.447
Probability	0.000000	0.000000

Table 3.2.1 Descriptive statistics of the estimated data

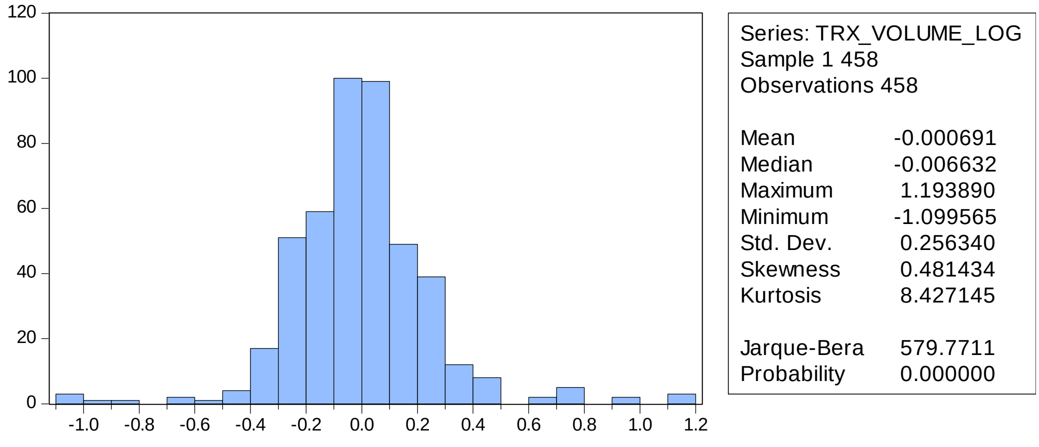

Figure 3.2.1 Histogram of Transaciton Volume Change

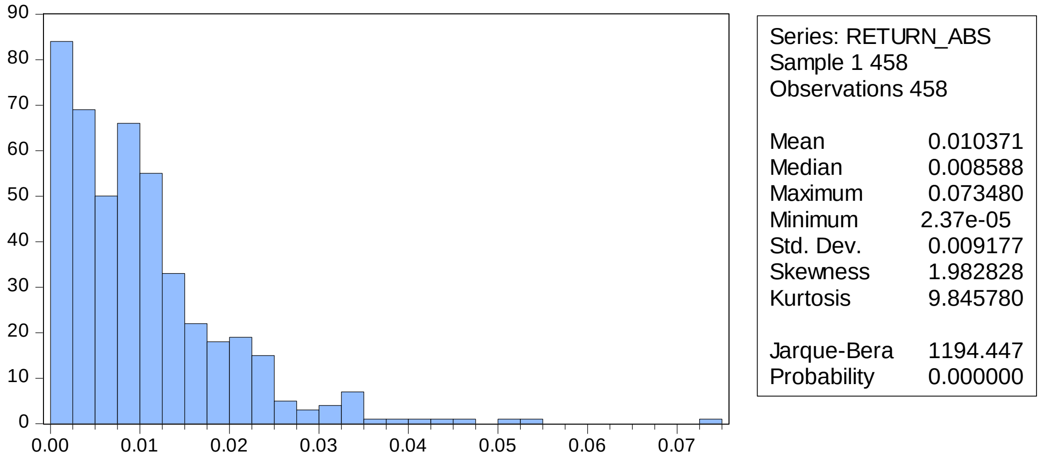

Figure 3.2.2 Histogram of Absolute Return

Deciding trends data had more steps compared to BIST data. Analysing trends data and stock market relation had some complexities like;

- detecting the words which reflect the demand in Borsa Istanbul,
- detecting whether the keyword needs filtering,
- deciding which location data to use,
- deciding the time scale(monthly,weekly,daily),
- deciding whether to take weekends/holidays into account or not.

In the beginning I decided that analysing 2015-2016 data was enough as Turkey had many political events, 2 general elections, strike and some stable intervals. I spent an important amount of time while detecting which keywords to use. It was required to check many keywords and to download, combine and normalize the 22 months' data (2015-2016) on hand would require an extensive operational effort. Instead of spending that effort, I developed code in R Language [39] and VisualBasic that downloads, combines and normalizes the data according to Equations 3.2.1 and 3.2.2.

The keywords chosen to be presented here were selected among the keyword list of keywords. The Table 3.2.2 below provides the keywords that I have checked and the explanation of the keyword usage.

Keywords	Parameter Description	Explanation
Usdtry	-	Might had an effect on BIST but at the first sight it did not, so I kept it aside and might be used later after digging deeper or in testing the estimation of USD TRY exchange rate in further works.
tl dolar	-	The same reason above
usd try	-	The same reason above
iş bankası hisse	-	This keyword is for stock of one of the biggest banks in Turkey however as stock and company had its private risks. Furthermore, the search volume data of the keyword was not stable(there were some impossible zeros in data) and considerably less compared to others. Therefore I decided not to show the results because of the space limitations.
Hisse	**$hisse_t$**: The 'hisse' keyword GTSVI logarithmic volume change of t^{th} day	'hisse' word is specific to Turkey and commonly it is used for stocks which seemed like a perfect word for analysis.
Bist	**$bist_t$**: The 'bist' keyword GTSVI logarithmic volume change of t^{th} day	As it is the new abbreviation of the Istanbul Stock Exchange Market, it is a perfect word however the search data included the German Language 'bist' as well. Therefore I needed to make some filtering. After implementing the constraint of Finance category.
borsa istanbul	**BI_t**: The 'borsa istanbul' keyword GTSVI logarithmic volume	It is the name of the stock exchange market and needed to be included.

	change of t^{th} day.	
bist+borsa istanbul	**BIB_t**: The 'borsa istanbul + bist' keyword GTSVI logarithmic volume change of t^{th} day.	Searched to combine mostly used two names of BIST.
bist+borsa istanbul+hisse	**$BIBH_t$**: The 'borsa istanbul + bist + hisse' keyword GTSVI logarithmic volume change of t^{th} day.	To check if both meaningful words would change the result.

Table 3.2.2 Descriptive statistics of the estimated data

As in GARCH method I needed stationary type data, I worked with the logarithmic changes of the trends data(DVC_t) which is calculated as follows for each explanatory variable;

$$DVC_t = \ln(\frac{DV_t}{DV_{t-1}})$$

After deciding the time interval and the keywords to be used, I needed to state which location to use. In order to include international search volume data as well, I did not put any region filtering. Trends data was available for all days of year, however BIST data was only available for non-holiday days. For the holiday i^{th} past data, I could take the average of the past data till the i^{th} past data order of BIST return data and accept it as t-i value but in that case I would lose the time specification of the i^{th} past data. Therefore, I decided to use directly i^{th} past data of trends return as the past data.

3.3. GARCH (Generalized Autoregressive Conditional Heteroscedasticity)

Volatility is an important factor in analysing the financial data. As I aim to analyse the financial time series in this study, I need to verify the explanatory variables are not significant due to the volatility in the data. Therefore I have to forecast the volatility and consider in the regression process. Autoregressive conditional heteroskedasticity (ARCH), generalized autoregressive conditional heteroskedasticity (GARCH) and stochastic volatility models are the main tools used to model and forecast volatility. As a result GARCH(1,1) model whose history is being told at next paragraph is chosen.

First, Engle (1982) [33] proposed a non-linear stationary model ARCH (Auto-Regressive Conditionally Heteroscedasticity) mentioning conditional variance of the parameters increases in an autoregressive way, that is t^{th} day variance is a function of $t\text{-}1^{th}$ day variance. Then Bollersev & Taylor (1986) [34] generalized the ARCH model and new generalized model was named it as GARCH (Auto-Regressive Conditionally Heteroscedasticity). GARCH is used if error terms are expected to show an autoregressive moving average behaviour and so it is for analysis of financial time series.

A GARCH Model is defined with p and q, which are the orders of σ^2 and ε^2. The notation of the model is provided below.

$$y_t = x_t' b + \varepsilon_t$$

$$\varepsilon_t | \varphi_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = w + \sum_{i=1}^{q} a_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2$$

A GARCH process is defined as follows:

Estimating the best fitting model with order q

$$y_t = a_0 + \sum_{i=1}^{q} a_i y_{t-i} + \varepsilon_t$$

Autocorrelations of ε^2 is calculated:

$$\rho = \frac{\sum_{t=i+1}^{T} (\hat{\varepsilon}_t^2 - \sigma_t^2)(\hat{\varepsilon}_{t-1}^2 - \sigma_{t-1}^2)}{\sum_{t=1}^{T} (\hat{\varepsilon}_t^2 - \sigma_t^2)^2}$$

The null hypothesis states that no ARCH or GARCH errors exist. Rejecting the hypothesis indicates the errors exist. The model specified to my study is given below:

$$y_t = a_0 + a_1 x_t + a_2 x_{t-1} + a_3 x_{t-2} + \varepsilon_t$$

$$\sigma_t^2 = w + a_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

In my model VC_t and AR_t corresponds to dependent variable y_t and $hisse_t$, BI_t, $bist_t$, BIB_t, $BIBH_t$ are the explanatory variables correspond to x_t based on the model I use.

4. Results

4.1. Results for ’hisse’ keyword

The keyword ‘hisse’ is a Turkish specific word for stock and a great ratio of searches with that keyword reflects the demand to any stock in stock market. It is a good indicator of stock market follower volume. I tested the significance of the trends data on transaction volume change and test results are given in the Table 4.1.1 below.

Dependent	VC_t	p-values
Constant	-0.04909	0.0003
$hisse_{-t}$	**0.127913**	0.0006
$hisse_{t-1}$	**0.224514**	0.0000
$hisse_{t-2}$	**0.074659**	0.0046
Variance Analysis		
C	0.028912	0.0000
ε_{t-1}^{2}	0.477981	0.0000
σ_{t-1}^{2}	0.056294	0.2264

Table 4.1.1 Regression results in BIST Transaction Volume Change estimation with 'hisse' search volume change.

The regression result shows that search volume changes at lag 1 and 2 are strongly significant in transaction volume change of BIST 100 data with $p<0.01$. Furthermore, lag 1 explanatory data is stronger from t in regression. The next step is to check if the data can explain index return as well. However, the change must be checked as absolute values of return as the change in search volume might be caused both by an expectation of rise or fall.

	AR_t	p-values
Constant	0.008748	0.0000
$hisse_{-t}$	**0.006449**	0.0000
$hisse_{t-1}$	**0.003646**	0.0001
$hisse_{t-2}$	**0.002124**	0.0159
Variance Analysis		
C	1.38E-06	0.0000
ε_{t-1}^{2}	-0.027984	0.0000
σ_{t-1}^{2}	1.013507	0.0000

Table 4.1.2 Regression results in BIST Absolute Return estimation with 'hisse' search volume change.

For absolute return 'hisse' search volume t and lag 1 are significant with $p<0.01$ strength and lag 2 data is significant with $p<0.02$. The coefficients of estimators have a positive relation with the absolute return data. Day t, which is the order (date) of the estimated data, seemed to be having a stronger relation when compared to other two.

4.2. Results for 'borsa istanbul' keyword

Keyword 'borsa istanbul' searches mean the searches that contained 'borsa' and 'istanbul' words in any order and again being the new name of the Istanbul Stock Exchange Market, it gives some explanation for the Transaction Volume Change. The test result of absolute return is avalible below in Table 4.2.1.

	VC_t	p-values
Constant	-0.01292	0.2744
BI_t	**0.039168**	0.0011
BI_{t-1}	**0.071039**	0.0000
BI_{t-2}	**0.041754**	0.0008
Variance Analysis		
C	0.031893	0.0000
ε_{t-1}^2	0.408575	0.0000
σ_{t-1}^2	0.095612	0.1179

Table 4.2.1 Regression results in BIST Transaction Volume Change estimation with 'borsa istanbul' search volume change.

Transaction volume change estimation with 'borsa istanbul' keyword volume changes again positive with t, lag 1 and lag 2 data that have $p<0.01$. Like 'hisse' keyword, the strongest explanation again belongs to lag 1. The test result of absolute return data with the same estimator variables is available in Table 4.2.2.

	AR_t	p-values
Constant	0.009430	0.0000
BI_t	**0.002283**	0.0001
BI_{t-1}	0.000914	0.1327
BI_{t-2}	**0.001258**	0.0092
Variance Analysis		
C	1.49E-06	0.0000
ε_{t-1}^2	-0.031149	0.0000
σ_{t-1}^2	1.016.108	0.0000

Table 4.2.2 Regression results in BIST Absolute Return estimation with 'borsa istanbul' search volume change.

Despite the volume of 'borsa istanbul' does not explain the dependents as strong as 'hisse', still the trends data t and lag 2 coefficients are significant in explaining the absolute return with $p<0.01$. The strongest explanatory variable is t for absolute return.

4.3. Results for 'bist' keyword

'bist' keyword, as it is the short name of the stock index is also taken into consideration in tests. Main searches that include 'bist' are results of irrelevant searches (mostly with German word 'bist'), so I applied finance category filtering (the filtering option provided by Google Trends API). The reason for this filtering is to exclude the effects other than finance. The transaction volume change estimation results are provided in Table 4.3.1 below.

	VC_t	p-values
Constant	0.001913	0.8631
$bist_t$	**0.021080**	0.0690
$bist_{t-1}$	**0.041597**	0.0047
Variance Analysis		
C	0.031538	0.0000
ε_{t-1}^2	0.042629	0.3458

σ_{t-1}^2	0.687765	0.0595

Table 4.3.1 Regression results in BIST Transaction Volume Change estimation with 'bist' search volume change.

The explanation capacity of 'bist' is not as much as two keywords above, however still the information it provides is consistent with the expectations. At lag 1 data is stronger in explaining transaction volume data with $p<0.01$ and at time t it is significant with $p <0.1$. Absolute return test results are provided in Table 4.3.2 below.

	AR_t	p-values
Constant	0.009995	0.0000
$bist_t$	**0.001880**	0.0002
$bist_{t-1}$	**0.002215**	0.0002
Variance Analysis		
C	2.21E-05	0.4082
ε_{t-1}^2	0.042629	0.3458
σ_{t-1}^2	0.687765	0.0595

Table 4.3.2 Regression results in BIST Absolute Return estimation with 'bist' search volume change.

The results indicate significance, at lag 1 level. The results show a strong relationship with $p<0.001$.

4.4. Results for 'bist + borsa istanbul' keyword

'bist' and 'borsa istanbul' keywords are the words that are used to search the stock index and their combination needed to be checked as their combination might indicate the stock market search information stronger compared to any of two. Transaction volume estimation results are given in the table below.

	VC_t	p-values

Constant	-0.00222	0.8538
BIB_t	**0.039042**	0.0061
BIB_{t-1}	**0.036431**	0.0347
BIB_{t-2}	0.018093	0.1582
Variance Analysis		
C	0.03263	0.0000
ε_{t-1}^2	0.427767	0.0000
σ_{t-1}^2	0.089394	0.0947

Table 4.4.1 Regression results in BIST Transaction Volume Change estimation with 'bist+borsa istanbul' search volume change.

Transaction volume change estimation coefficients of t ($p<0.01$) and lag 1 ($p<0.05$) are significant and consistent with the findings for other keywords. However, the comparative strength of lag 1 compared to t seems to disappear when this keyword is used. Absolute return estimation result is available below.

	AR_t	p-values
Constant	0.009858	0.0000
BIB_t	**0.001396**	0.0074
BIB_{t-1}	**0.001036**	0.0613
BIB_{t-2}	0.000367	0.4698
Variance Analysis		
C	1.67E-06	0.0000
ε_{t-1}^2	-0.034110	0.0000
σ_{t-1}^2	1.016967	0.0000

Table 4.4.2 Regression results in BIST Absolute Return estimation with 'bist+borsa istanbul' search volume change.

At absolute return estimation t and lag 1 volume changes seems significant with $p<0.01$ and $p<0.1$ respectively.

4.5. Results for ‘bist + borsa istanbul + hisse’ keyword

To test the combination of all the meaningful keywords’ search volume change, the data for the three keywords ‘bist’, ’borsa istanbul’ and ’hisse’ tested on volume change and the results are given in the Table 4.5.1.

	VC_t	p-values
Constant	-0.018697	0.1084
$BIBH_t$	**0.057789**	0.0002
$BIBH_{t-1}$	**0.077611**	0.0000
Variance Analysis		
C	0.032721	0.0000
ε_{t-1}^2	0.414848	0.0000
σ_{t-1}^2	0.068952	0.1471

Table 4.5.1 Regression results in BIST Transaction Volume Change estimation with ‘hisse+bist+borsa istanbul’ search volume change.

This combination indicates a regression without lag 2 data like ‘bist’ and ‘bist+borsa istanbul’ keywords does. The high significance levels $p<0.01$ is consistent with other keyword search volumes. Lag1 data is again a stronger predictor compared to t. Absolute return estimation result is available below.

	AR_t	p-values
Constant	0.009655	0.0000
$BIBH_t$	**0.002169**	0.0000
$BIBH_{t-1}$	**0.001876**	0.0000
Variance Analysis		
C	1.07E-06	0.0000
ε_{t-1}^2	-0.025721	0.0000
σ_{t-1}^2	1015351	0.0000

Table 4.5.2 Regression results in BIST Absolute Return estimation with ‘hisse+bist+borsa istanbul’ search volume change.

For absolute return estimation both t and lag 1 data coefficients are highly significant with $p<0.0001$.

5. Conclusion

Efficient Markets Hypothesis that Fama presented in 1970 states that even in the weak form, the market's current price reflects all publicly available information in the past and therefore no estimation could be feasible for the estimation of the market with past and publicly available data. However, stock markets estimation studies went on with day-by-day growing numbers. Results of the studies indicate that market is fast for including the information in the prices but it is not as fast as preventing profit to the past data analysts. Markets finally will include a type of past data however, another type of data would replace it and there will be a new estimation opportunity. Recent researches show that internet data is now the data type that provides some estimation advantages.

Starting from Wysocki [1] many of the researchers observed explanatory relationship from internet data towards stock markets. The research models and results change according to the internet source researches used like finance specific messaging boards, web search data, newspapers, economic magazines and public messaging platforms. Researches also differentiate in the way they process data namely focusing on message volumes, search volumes or the content sentiment.

The aim of this research is to contribute on literature as being the first work that is prepared on Istanbul Stock Market and Google Trends search data relationship by checking the significance of the t-i trends data in estimation. During the study, I tested many possible keywords that directly or indirectly indicate the demand to BIST. I expected that some of the words might reflect the demand to stock market more than others do. It was correct but in a way result was surprising that not the direct keywords that first come into the mind like 'bist'and 'borsa istanbul' were less successful than the keyword 'hisse' which simply is the Turkish specific word for stock.

The results show that some keywords predict better than others but for all the keywords, I find that using web search data as predictor help to improve estimation for transaction volume and absolute return data of Istanbul Stock Market Index (BIST). Taking absolute return and transaction volume changes as dependent variables, search data at lag 1 and 2 is significant.

6. References

1. Antweiler, W.; Frank, M. Z. (2004), Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards, The Journal of Finance, Vol. 59, No. 3, pp. 1259-1294

2. Asur, S.; Huberman, B. (2011) Predicting the future with social media, … Agent Technology (WI-IAT), 2010 IEEE, pp.492–499.

3. Bar-Haim, R.; Dinur, E.; Feldman, R.; Fresko, M.; Goldstein, G. (2011) Identifying and following expert investors in stock microblogs, EMNLP '11 Proceedings of the Conference on Empirical Methods in Natural Language Processing, Pages 1310-1319

4. Beer, F.; Herve, F.; Zouaoui M. (2013) Google Investor Sentiment and the Stock Market, Economic Bulletin, Vol.33 no.1 pp. 454-466.

5. Bollen, J.; Mao, H.; Zeng, X. (2011), Twitter mood predicts the stock market, Journal of Computational Science, 2(1), pp.1–8.

6. Bollerslev, T. (1986), Generalized autoregressive conditional heteroscedasticity, Journal of Econometrics, 1986, vol. 31, issue 3, pages 307-327.

7. Bommel, J. (2003), Rumors. The Journal of Finance, 58(4), pp.1499–1519.

8. Choi, H.; Varian, H. (2012), Predicting the Present with Google Trends, Economic Record, 88: 2–9, doi:10.1111/j.1475-4932.

9. Chowdhury, S.G.; Routh, S.; Chakrabarti, S. (2014), News Analytics and Sentiment Analysis to Predict Stock Price Trends, Int. J. Comput. Sci. Inform. Technol 5.3 (2014): 3595-3604.

10. DeBondt, W. F. M.; Richard Thaler (1995), “Does the Stock Market Overreact?” Journal of Finance, 40, 793-805.

11. Dewally, M. (2000), Internet Investment Advice: Investing with a Rock of Salt, Financial Analysts Journal

12. Engle, Robert F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", Econometrica, 50 (4): 987–1007, JSTOR 1912773.

13. Fama, E. F.; Malkiel, B. G. (1970), Efficient Capital Markets: A Review of Theory and Empirical Work, The Journal of Finance, 25: 383–417. doi:10.1111/j.1540-6261.

14. Gu, B.; Konana, P.; Liu, A.; Rajagopalan, B.; Ghosh, J. (2006), Identifying Information in Stock Message Boards and Its Implications for Stock Market Efficiency, Extended Abstract for Consideration for WISE

15. Gündüz, H.; Çataltepe, Z. (2015) "Borsa Istanbul (BIST) daily estimation using financial news and balanced feature selection." Expert Syst. Appl. 42 (2015): 9001-9011.

16. Ishima, H.; Kazumi, T.; Maeda, A. (2014), Sentiment Analysis for the Japanese stock market, DOI: http://dx.doi.org/10.1504/GBER.2015.070303

17. Joshi, K.; Bharati, H. N.; Jyothi, R. (2015), Stock Trend Estimation Using News Sentiment Analysis, arXiv:1607.01958 [cs.CL].

18. Kahneman, D., Slovic, P., & Tversky, A. (1982). Judgment under uncertainty: Heuristics and biases. Cambridge: Cambridge University Press.

19. Levenberg, A.; Pulman, S.; Moilanen, K.; Simpson, E.; Roberts, S. (2013), Predicting Economic Indicators from Web Text Using Sentiment Composition, IJCCE 2014 Vol.3(2): 109-115 ISSN: 2010-3743

20. Loughlin, C.; Harnisch, E. (2013), The Viability of StockTwits and Google Trends to Predict the Stock Market, stocktwits.com/research/Viability-of-StockTwits-and-Google-Trends-Loughlin_Harnisch.pdf.

21. Malkiel, Burton G. (1973), A Random Walk Down Wall Street (6th ed.). W.W. Norton & Company, Inc. ISBN 0-393-06245-7.

22. Malkiel, Burton G. (2003), "The Efficient Market Hypothesis and Its Critics" Journal of Economic Perspectives, 17(1): 59-82.

23. Mao, H.; Counts, S.; Bollen, J. (2011), Predicting Financial Markets: Comparing Survey, News, Twitter and Search Engine Data, arXiv preprint p.10.

24. Öztürk, S.; Çiftçi, K. (2014), A Sentiment Analysis of Twitter Content as a Predictor of Exchange Rate Movements, Review of Economic Analysis 6, 132-140, 1973-3909/2014132.

25. Posedel, P. (2005), Properties and Estimation of GARCH (1,1) Model, Metodoloski Zvezki, Vol. 2, No. 2, 2005, 243-257.

26. Preis, T.; Maat, H. S.; Stanley, H. E. (2013), Quantifying Trading Behavior in Financial Markets Using Google Trends, Scientific Reports 3, Article number: 1684, doi:10.1038/srep01684.

27. Rao, T.; Srivastava, S. (2013), Modelling Movements in Oil, Gold, Forex and Market Indices Using Search Volume Index and Twitter Sentiments. In Proceedings of the 5th Annual ACM Web Science Conference.

28. Ruiz, E. J.; Hristidis, V.; Castillo, C.; Gionis, A.; Jaimes, A. (2012), Correlating Financial Time Series with Micro-Blogging Activity, Proceeding WSDM '12 Proceedings of the fifth ACM international conference on Web search and data mining, Pages 513-522

29. Shiller, R. J. (2000), Irrational exuberance. Princeton, NJ: Princeton University Press.

30. Sprenger, T.O.; Welpe, I. M. (2010), Tweets and Trades: The Information Content of Stock Microblogs, European Financial Management, 20(5), 926-957

31. Tayal, D.; Komaragiri, S. (2009) Comparative Analysis of the Impact of Blogging and Micro-blogging on Market Performance, International Journal, 1(3), pp.176–182.

32. Tumarkin, R.; Whitelaw, R.F. (2001), News or Noise? Internet Postings and Stock Prices. Financial Analysts Journal, 57(3), pp.41–51

33. Vincent, A.; Armstrong, M. (2010), Predicting Break-Points in Trading Strategies with Twitter, SSRN 1685150.

34. Wysocki, P. D. (1998), University of Michigan Business School Working Paper No. 98025

35. Zhang, X.; Fuehres, H.; Gloor, P. A. (2011), Predicting Stock Market Indicators through Twitter "I hope it is not as bad as I fear", Social and Behavioural Sciences Volume 26, Pages 55-62

36. www.google.com/trends

37. www.investing.com

38. www.netmarketshare.com/search-engine-market-share.aspx

39. erikjohansson.blogspot.com.tr

7. Appendix

7.1. Results for ’hisse’ keyword

7.1.1. Transaction Volume Change Regression Result

Dependent Variable: TRX_VOLUME_LOG
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 14:34
Sample: 1 458
Included observations: 458
Convergence achieved after 23 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.049093	0.013621	-3.604282	0.0003
HISSE_LOG_T	0.127913	0.037305	3.428850	0.0006
HISSE_LOG_1	0.224514	0.028457	7.889691	0.0000
HISSE_LOG_2	0.074659	0.026358	2.832533	0.0046
	Variance Equation			
C	0.028912	0.002833	10.20373	0.0000
RESID(-1)^2	0.477981	0.080660	5.925860	0.0000
GARCH(-1)	0.056294	0.046537	1.209663	0.2264

R-squared	0.099392	Mean dependent var	-0.000691
Adjusted R-squared	0.093441	S.D. dependent var	0.256340
S.E. of regression	0.244070	Akaike info criterion	-0.185400
Sum squared resid	27.04490	Schwarz criterion	-0.122326
Log likelihood	49.45666	Hannan-Quinn criter.	-0.160558
Durbin-Watson stat	2.504249		

7.1.2. Absolute Return Regression Result

Dependent Variable: RETURN_ABS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 14:30
Sample: 1 458
Included observations: 458
Convergence achieved after 49 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.008748	0.000162	53.92011	0.0000
HISSE_LOG_T	0.006449	0.001089	5.923869	0.0000
HISSE_LOG_1	0.003646	0.000931	3.917146	0.0001
HISSE_LOG_2	0.002124	0.000881	2.410975	0.0159

	Variance Equation			
C	1.38E-06	2.36E-07	5.829889	0.0000
RESID(-1)^2	-0.027984	0.003269	-8.561148	0.0000
GARCH(-1)	1.013507	0.004588	220.8827	0.0000

R-squared	0.048633	Mean dependent var	0.010371
Adjusted R-squared	0.042347	S.D. dependent var	0.009177
S.E. of regression	0.008981	Akaike info criterion	-6.640184
Sum squared resid	0.036619	Schwarz criterion	-6.577109
Log likelihood	1527.602	Hannan-Quinn criter.	-6.615342
Durbin-Watson stat	2.095596		

7.2. Results for ’borsa istanbul’ keyword

7.2.1. Transaction Volume Change Regression Result

Dependent Variable: TRX_VOLUME_LOG
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 15:04
Sample: 1 458
Included observations: 458
Convergence achieved after 41 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.012918	0.011818	-1.093058	0.2744
BI_LOG_T	0.039168	0.011987	3.267580	0.0011
BI_LOG_1	0.071039	0.016569	4.287545	0.0000
BI_LOG_2	0.041754	0.012506	3.338672	0.0008
	Variance Equation			
C	0.031893	0.003704	8.609722	0.0000
RESID(-1)^2	0.408575	0.079785	5.120959	0.0000
GARCH(-1)	0.095612	0.061151	1.563541	0.1179

R-squared	0.034063	Mean dependent var	-0.000691
Adjusted R-squared	0.027680	S.D. dependent var	0.256340
S.E. of regression	0.252768	Akaike info criterion	-0.087064
Sum squared resid	29.00673	Schwarz criterion	-0.023989
Log likelihood	26.93763	Hannan-Quinn criter.	-0.062222
Durbin-Watson stat	2.476171		

7.2.2. Absolute Return Regression Result

Dependent Variable: RETURN_ABS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 15:00
Sample: 1 458
Included observations: 458
Convergence achieved after 33 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009430	1.00E-05	940.6471	0.0000
BI_LOG_T	0.002283	0.000591	3.863759	0.0001
BI_LOG_1	0.000914	0.000608	1.503695	0.1327
BI_LOG_2	0.001258	0.000483	2.605283	0.0092
	Variance Equation			
C	1.49E-06	2.48E-07	5.999763	0.0000
RESID(-1)^2	-0.031149	0.003393	-9.179998	0.0000
GARCH(-1)	1.016108	0.005567	182.5370	0.0000

R-squared	0.033383	Mean dependent var	0.010371
Adjusted R-squared	0.026996	S.D. dependent var	0.009177
S.E. of regression	0.009053	Akaike info criterion	-6.637759
Sum squared resid	0.037206	Schwarz criterion	-6.574684
Log likelihood	1527.047	Hannan-Quinn criter.	-6.612917
Durbin-Watson stat	2.081535		

7.3. Results for ’bist’ keyword

7.3.1. Transaction Volume Change Regression Result

Dependent Variable: TRX_VOLUME_LOG
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/15/17 Time: 23:30
Sample: 1 458
Included observations: 458
Convergence achieved after 29 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001913	0.011096	0.172368	0.8631
BIST_LOG_T	0.021080	0.011592	1.818498	0.0690
BIST_LOG_1	0.041597	0.014712	2.827447	0.0047
	Variance Equation			

C	0.031538	0.003725	8.466430	0.0000
RESID(-1)^2	0.454995	0.081039	5.614542	0.0000
GARCH(-1)	0.092619	0.052931	1.749790	0.0802

R-squared	0.008785	Mean dependent var	-0.000691
Adjusted R-squared	0.004428	S.D. dependent var	0.256340
S.E. of regression	0.255772	Akaike info criterion	-0.067682
Sum squared resid	29.76580	Schwarz criterion	-0.013618
Log likelihood	21.49918	Hannan-Quinn criter.	-0.046389
Durbin-Watson stat	2.459987		

7.3.2. Absolute Return Regression Result

Dependent Variable: RETURN_ABS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/15/17 Time: 23:28
Sample: 1 458
Included observations: 458
Convergence achieved after 58 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009995	0.000553	18.06915	0.0000
BIST_LOG_T	0.001880	0.000512	3.672521	0.0002
BIST_LOG_1	0.002215	0.000598	3.705302	0.0002
	Variance Equation			
C	2.21E-05	2.67E-05	0.827123	0.4082
RESID(-1)^2	0.042629	0.045215	0.942806	0.3458
GARCH(-1)	0.687765	0.364913	1.884736	0.0595

R-squared	0.025820	Mean dependent var	0.010371
Adjusted R-squared	0.021538	S.D. dependent var	0.009177
S.E. of regression	0.009078	Akaike info criterion	-6.559201
Sum squared resid	0.037497	Schwarz criterion	-6.505137
Log likelihood	1508.057	Hannan-Quinn criter.	-6.537908
Durbin-Watson stat	2.149467		

7.4. Results for ’bist + borsa istanbul’ keyword

7.4.1. Transaction Volume Change Regression Result

Dependent Variable: TRX_VOLUME_LOG
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 17:20
Sample: 1 458
Included observations: 458
Convergence achieved after 126 iterations

Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002220	0.012050	-0.184279	0.8538
BI_BIST_T	0.039042	0.014236	2.742510	0.0061
BI_BIST_1	0.036431	0.017250	2.111927	0.0347
BI_BIST_2	0.018093	0.012820	1.411255	0.1582
	Variance Equation			
C	0.032625	0.003471	9.399129	0.0000
RESID(-1)^2	0.427767	0.075068	5.698429	0.0000
GARCH(-1)	0.089394	0.053491	1.671184	0.0947

R-squared	0.011464	Mean dependent var	-0.000691
Adjusted R-squared	0.004932	S.D. dependent var	0.256340
S.E. of regression	0.255707	Akaike info criterion	-0.063605
Sum squared resid	29.68535	Schwarz criterion	-0.000531
Log likelihood	21.56560	Hannan-Quinn criter.	-0.038763
Durbin-Watson stat	2.456221		

7.4.2. Absolute Return Regression Result

Dependent Variable: RETURN_ABS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 17:18
Sample: 1 458
Included observations: 458
Convergence achieved after 71 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009858	1.60E-05	615.6393	0.0000
BI_BIST_T	0.001396	0.000521	2.679613	0.0074
BI_BIST_1	0.001036	0.000554	1.871321	0.0613
BI_BIST_2	0.000367	0.000507	0.722767	0.4698
	Variance Equation			
C	1.67E-06	2.01E-07	8.319111	0.0000
RESID(-1)^2	-0.034110	0.003692	-9.239117	0.0000
GARCH(-1)	1.016967	0.004589	221.6168	0.0000

R-squared	0.028539	Mean dependent var	0.010371
Adjusted R-squared	0.022120	S.D. dependent var	0.009177
S.E. of regression	0.009075	Akaike info criterion	-6.633306
Sum squared resid	0.037393	Schwarz criterion	-6.570231
Log likelihood	1526.027	Hannan-Quinn criter.	-6.608464
Durbin-Watson stat	2.119816		

7.5. Results for 'bist + borsa istanbul + hisse' keyword

7.5.1. Transaction Volume Change Regression Result

Dependent Variable: TRX_VOLUME_LOG
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 17:27
Sample: 1 458
Included observations: 458
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.018697	0.011647	-1.605246	0.1084
BBH_LOG_T	0.057789	0.015327	3.770454	0.0002
BBH_LOG_1	0.077611	0.016071	4.829127	0.0000
	Variance Equation			
C	0.032721	0.002948	11.10108	0.0000
RESID(-1)^2	0.414848	0.073084	5.676316	0.0000
GARCH(-1)	0.068952	0.047561	1.449745	0.1471

R-squared	0.061996	Mean dependent var	-0.000691
Adjusted R-squared	0.057872	S.D. dependent var	0.256340
S.E. of regression	0.248812	Akaike info criterion	-0.105936
Sum squared resid	28.16791	Schwarz criterion	-0.051872
Log likelihood	30.25936	Hannan-Quinn criter.	-0.084643
Durbin-Watson stat	2.439191		

7.5.2. Absolute Return Regression Result

Dependent Variable: RETURN_ABS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/10/17 Time: 17:23
Sample: 1 458
Included observations: 458
Convergence achieved after 54 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.009655	4.51E-05	214.0534	0.0000
BBH_LOG_T	0.002169	0.000531	4.083249	0.0000
BBH_LOG_1	0.001876	0.000104	18.12075	0.0000
	Variance Equation			
C	1.07E-06	1.81E-07	5.913251	0.0000
RESID(-1)^2	-0.025721	0.003221	-7.984487	0.0000
GARCH(-1)	1.015351	0.004615	219.9925	0.0000

R-squared	0.033673	Mean dependent var	0.010371
Adjusted R-squared	0.029425	S.D. dependent var	0.009177
S.E. of regression	0.009041	Akaike info criterion	-6.632043
Sum squared resid	0.037195	Schwarz criterion	-6.577979
Log likelihood	1524.738	Hannan-Quinn criter.	-6.610750
Durbin-Watson stat	2.077413		

7.6. Top searches with keywords

7.6.1. ‘bist + borsa istanbul‘ Top Searches

bist 100	Breakout
bist 30	Breakout
bist canlı	Breakout
bist işlem saatleri	Breakout
garanti bist	Breakout

7.6.2. ‘bist + borsa istanbul + hisse’ Top Searches

bist 100	Breakout
mynet hisse	Breakout
hisse net	+450%
deniz yatırım	+50%
deniz yatırım hisse	+50%
hisse önerileri	+40%

7.6.3. ‘hisse’ Top Searches

bigpara	Breakout
hisse net	Breakout
hisse net forum	Breakout
bigpara hisse	+1,450%
mynet hisse	+1,450%
hisse yorumları	+1,200%
hisse yorum	+650%
hisse forum	+200%
hisse analiz	+100%

7.7. Data

The data is available in the file given below.

data.xlsx

7.7.1. Data Dictionary

The data dictionary is available in the table below.

Parameter	Explanation
date	Daily date specificator of data
return	Daily return of BIST100 Index
return_abs	Daily absolute return of BIST100 Index
trx_volume_log	Daily transaction volume change
hisse_log_p1	Daily 'hisse' logarithmic changes of t plus 1
hisse_log_t	Daily 'hisse' logarithmic changes of t
hisse_log-1	Daily 'hisse' logarithmic changes of t -1
hisse_log-2	Daily 'hisse' logarithmic changes of t -2
hisse_log-3	Daily 'hisse' logarithmic changes of t -3
hisse_log-4	Daily 'hisse' logarithmic changes of t -4
hisse_log-5	Daily 'hisse' logarithmic changes of t -5
hisse_log-6	Daily 'hisse' logarithmic changes of t -6
bi_log_p1	Daily 'borsa istanbul' logarithmic changes of t plus 1
bi_log_t	Daily 'borsa istanbul' logarithmic changes of t
bi_log_1	Daily 'borsa istanbul' logarithmic changes of t -1
bi_log_2	Daily 'borsa istanbul' logarithmic changes of t -2
bi_log_3	Daily 'borsa istanbul' logarithmic changes of t -3
bi_log_4	Daily 'borsa istanbul' logarithmic changes of t -4
bi_log_5	Daily 'borsa istanbul' logarithmic changes of t -5
bi_log_6	Daily 'borsa istanbul' logarithmic changes of t -6
bi_bist_p1	Daily 'bist+borsa istanbul' logarithmic changes of t plus 1
bi_bist_t	Daily 'bist+borsa istanbul' logarithmic changes of t
bi_bist_1	Daily 'bist+borsa istanbul' logarithmic changes of t -1
bi_bist_2	Daily 'bist+borsa istanbul' logarithmic changes of t -2
bi_bist_3	Daily 'bist+borsa istanbul' logarithmic changes of t -3
bi_bist_4	Daily 'bist+borsa istanbul' logarithmic changes of t -4
bi_bist_5	Daily 'bist+borsa istanbul' logarithmic changes of t -5
bi_bist_6	Daily 'bist+borsa istanbul' logarithmic changes of t -6
bbh_log_p1	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t plus 1
bbh_log_t	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t
bbh_log-1	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -1
bbh_log-2	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -2
bbh_log-3	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -3
bbh_log-4	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -4
bbh_log-5	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -5
bbh_log-6	Daily 'bist+borsa istanbul+hisse' logarithmic changes of t -6
bist_log_p1	Daily 'bist' logarithmic changes of t plus 1
bist_log_t	Daily 'bist' logarithmic changes of t
bist_log_1	Daily 'bist' logarithmic changes of t -1
bist_log_2	Daily 'bist' logarithmic changes of t -2
bist_log_3	Daily 'bist' logarithmic changes of t -3
bist_log_4	Daily 'bist' logarithmic changes of t -4
bist_log_5	Daily 'bist' logarithmic changes of t -5
bist_log_6	Daily 'bist' logarithmic changes of t -6

7.7.2. Data used for tests

The return, volume change, 'hisse' search volume change data and absolute return data is given below. The remaining data is available in attached file.

Date	Return	return_abs	hisse_log_t	hisse_log-1	hisse_log-2
5.1.2015	0.0117	0.0117	0.8611	-0.3162	-0.4673
6.1.2015	0.0052	0.0052	-0.1559	0.8611	-0.3162
7.1.2015	-0.0015	0.0015	0.1863	-0.1559	0.8611
8.1.2015	0.0105	0.0105	-0.1278	0.1863	-0.1559
9.1.2015	-0.0005	0.0005	0.0000	-0.1278	0.1863
12.1.2015	0.0025	0.0025	0.5341	0.4303	-0.8938
13.1.2015	0.0051	0.0051	0.0984	0.5341	0.4303
14.1.2015	-0.0085	0.0085	-0.0317	0.0984	0.5341
15.1.2015	0.0020	0.0020	-0.1259	-0.0317	0.0984
16.1.2015	-0.0037	0.0037	-0.2171	-0.1259	-0.0317
19.1.2015	0.0067	0.0067	0.5295	0.1658	-0.4761
20.1.2015	0.0135	0.0135	0.0852	0.5295	0.1658
21.1.2015	0.0124	0.0124	-0.0852	0.0852	0.5295
22.1.2015	0.0065	0.0065	0.0852	-0.0852	0.0852
23.1.2015	-0.0018	0.0018	-0.1306	0.0852	-0.0852
26.1.2015	0.0074	0.0074	0.6103	0.0667	-0.7408
27.1.2015	-0.0029	0.0029	0.0829	0.6103	0.0667
28.1.2015	-0.0089	0.0089	-0.0347	0.0829	0.6103
29.1.2015	-0.0199	0.0199	-0.1522	-0.0347	0.0829
30.1.2015	0.0044	0.0044	0.0270	-0.1522	-0.0347
2.2.2015	0.0086	0.0086	0.9430	0.0174	-0.6539
3.2.2015	-0.0249	0.0249	-0.1350	0.9430	0.0174
4.2.2015	-0.0184	0.0184	0.1029	-0.1350	0.9430
5.2.2015	-0.0014	0.0014	-0.0445	0.1029	-0.1350
6.2.2015	-0.0094	0.0094	-0.0706	-0.0445	0.1029
9.2.2015	-0.0049	0.0049	0.2877	-0.0866	-0.4555
10.2.2015	-0.0174	0.0174	0.1112	0.2877	-0.0866
11.2.2015	0.0038	0.0038	0.1579	0.1112	0.2877
12.2.2015	0.0313	0.0313	0.1165	0.1579	0.1112
13.2.2015	-0.0032	0.0032	-0.2485	0.1165	0.1579
16.2.2015	0.0027	0.0027	0.6206	0.0705	-0.4649
17.2.2015	-0.0190	0.0190	-0.0783	0.6206	0.0705
18.2.2015	0.0120	0.0120	-0.0355	-0.0783	0.6206
19.2.2015	0.0113	0.0113	0.0698	-0.0355	-0.0783
20.2.2015	-0.0108	0.0108	-0.0698	0.0698	-0.0355
23.2.2015	0.0093	0.0093	0.7432	-0.3126	-0.4299
24.2.2015	0.0047	0.0047	0.0359	0.7432	-0.3126
25.2.2015	0.0005	0.0005	0.0899	0.0359	0.7432
26.2.2015	-0.0095	0.0095	-0.1018	0.0899	0.0359

27.2.2015	-0.0208	0.0208	-0.0120	-0.1018	0.0899
2.3.2015	-0.0024	0.0024	0.7274	-0.1235	-0.5476
3.3.2015	0.0042	0.0042	-0.0343	0.7274	-0.1235
4.3.2015	-0.0269	0.0269	-0.0849	-0.0343	0.7274
5.3.2015	-0.0158	0.0158	0.2357	-0.0849	-0.0343
6.3.2015	-0.0058	0.0058	-0.2485	0.2357	-0.0849
9.3.2015	0.0042	0.0042	0.6391	-0.1610	-0.5281
10.3.2015	-0.0336	0.0336	0.2772	0.6391	-0.1610
11.3.2015	0.0038	0.0038	-0.0652	0.2772	0.6391
12.3.2015	0.0002	0.0002	0.0547	-0.0652	0.2772
13.3.2015	-0.0213	0.0213	-0.1245	0.0547	-0.0652
16.3.2015	0.0201	0.0201	0.7351	-0.1304	-0.6576
17.3.2015	0.0232	0.0232	0.0533	0.7351	-0.1304
18.3.2015	-0.0011	0.0011	0.0750	0.0533	0.7351
19.3.2015	0.0245	0.0245	-0.0881	0.0750	0.0533
20.3.2015	0.0071	0.0071	0.0260	-0.0881	0.0750
23.3.2015	0.0149	0.0149	0.6373	0.1202	-0.6931
24.3.2015	-0.0206	0.0206	-0.0116	0.6373	0.1202
25.3.2015	0.0075	0.0075	-0.1105	-0.0116	0.6373
26.3.2015	-0.0142	0.0142	0.2412	-0.1105	-0.0116
27.3.2015	-0.0072	0.0072	-0.1661	0.2412	-0.1105
30.3.2015	0.0158	0.0158	1.0176	-0.4040	-0.5902
31.3.2015	-0.0164	0.0164	-0.1847	1.0176	-0.4040
1.4.2015	0.0045	0.0045	0.0564	-0.1847	1.0176
2.4.2015	0.0057	0.0057	0.0790	0.0564	-0.1847
3.4.2015	0.0160	0.0160	0.0126	0.0790	0.0564
6.4.2015	0.0016	0.0016	0.6042	0.1749	-0.6685
7.4.2015	-0.0080	0.0080	-0.2202	0.6042	0.1749
8.4.2015	0.0040	0.0040	0.1097	-0.2202	0.6042
9.4.2015	0.0086	0.0086	0.0870	0.1097	-0.2202
10.4.2015	-0.0104	0.0104	-0.0120	0.0870	0.1097
13.4.2015	-0.0086	0.0086	0.8473	-0.1189	-0.7813
14.4.2015	0.0047	0.0047	-0.0364	0.8473	-0.1189
15.4.2015	-0.0118	0.0118	0.0000	-0.0364	0.8473
16.4.2015	0.0132	0.0132	0.1803	0.0000	-0.0364
17.4.2015	-0.0002	0.0002	-0.1803	0.1803	0.0000
20.4.2015	-0.0014	0.0014	0.8979	-0.2147	-0.7056
21.4.2015	0.0237	0.0237	0.1905	0.8979	-0.2147
22.4.2015	-0.0059	0.0059	-0.2283	0.1905	0.8979
24.4.2015	0.0209	0.0209	0.5371	-0.5500	-0.2283
27.4.2015	0.0099	0.0099	0.8858	-0.1964	-0.4520
28.4.2015	-0.0022	0.0022	-0.3262	0.8858	-0.1964
29.4.2015	-0.0027	0.0027	0.3567	-0.3262	0.8858
30.4.2015	-0.0239	0.0239	-0.2485	0.3567	-0.3262
4.5.2015	0.0009	0.0009	0.7291	0.2601	-0.3037
5.5.2015	-0.0076	0.0076	0.0347	0.7291	0.2601

6.5.2015	-0.0113	0.0113	0.0225	0.0347	0.7291
7.5.2015	0.0016	0.0016	-0.1560	0.0225	0.0347
8.5.2015	0.0179	0.0179	0.0506	-0.1560	0.0225
11.5.2015	0.0082	0.0082	0.8916	0.0296	-0.7309
12.5.2015	0.0072	0.0072	-0.2357	0.8916	0.0296
13.5.2015	0.0123	0.0123	0.1079	-0.2357	0.8916
14.5.2015	0.0095	0.0095	0.0870	0.1079	-0.2357
15.5.2015	0.0041	0.0041	0.0000	0.0870	0.1079
18.5.2015	0.0119	0.0119	0.9575	-0.1829	-0.7357
20.5.2015	-0.0098	0.0098	0.7638	-0.8815	0.9575
21.5.2015	-0.0141	0.0141	0.0974	0.7638	-0.8815
22.5.2015	-0.0088	0.0088	-0.1803	0.0974	0.7638
25.5.2015	-0.0145	0.0145	0.7037	0.0048	-0.5658
26.5.2015	-0.0109	0.0109	-0.1844	0.7037	0.0048
27.5.2015	0.0077	0.0077	0.0494	-0.1844	0.7037
28.5.2015	-0.0086	0.0086	-0.1014	0.0494	-0.1844
29.5.2015	-0.0071	0.0071	0.1598	-0.1014	0.0494
1.6.2015	-0.0312	0.0312	0.4911	0.0271	-0.7885
2.6.2015	0.0122	0.0122	0.0858	0.4911	0.0271
3.6.2015	0.0239	0.0239	-0.0420	0.0858	0.4911
4.6.2015	-0.0108	0.0108	0.1210	-0.0420	0.0858
5.6.2015	-0.0068	0.0068	-0.1353	0.1210	-0.0420
8.6.2015	-0.0518	0.0518	1.1712	-0.1744	-0.6232
9.6.2015	0.0044	0.0044	-0.2231	1.1712	-0.1744
10.6.2015	0.0203	0.0203	0.0247	-0.2231	1.1712
11.6.2015	0.0137	0.0137	-0.0247	0.0247	-0.2231
12.6.2015	-0.0039	0.0039	-0.2549	-0.0247	0.0247
15.6.2015	-0.0198	0.0198	0.6774	0.2138	-0.8690
16.6.2015	0.0155	0.0155	0.0465	0.6774	0.2138
17.6.2015	0.0066	0.0066	-0.0308	0.0465	0.6774
18.6.2015	0.0150	0.0150	0.0155	-0.0308	0.0465
19.6.2015	0.0064	0.0064	0.0597	0.0155	-0.0308
22.6.2015	0.0117	0.0117	0.8431	0.0285	-0.8329
23.6.2015	-0.0043	0.0043	-0.1068	0.8431	0.0285
24.6.2015	0.0128	0.0128	-0.0142	-0.1068	0.8431
25.6.2015	-0.0103	0.0103	0.1335	-0.0142	-0.1068
26.6.2015	0.0032	0.0032	-0.2076	0.1335	-0.0142
29.6.2015	-0.0217	0.0217	1.0217	-0.3241	-0.5108
30.6.2015	0.0060	0.0060	-0.0834	1.0217	-0.3241
1.7.2015	-0.0069	0.0069	0.1603	-0.0834	1.0217
2.7.2015	0.0024	0.0024	0.2107	0.1603	-0.0834
3.7.2015	-0.0081	0.0081	-0.2357	0.2107	0.1603
6.7.2015	0.0140	0.0140	0.7213	-0.1450	-0.6082
7.7.2015	-0.0097	0.0097	0.0671	0.7213	-0.1450
8.7.2015	-0.0146	0.0146	-0.1391	0.0671	0.7213
9.7.2015	0.0234	0.0234	0.1391	-0.1391	0.0671

10.7.2015	0.0061	0.0061	0.0129	0.1391	-0.1391
13.7.2015	0.0072	0.0072	0.8427	-0.1823	-0.6678
14.7.2015	-0.0042	0.0042	0.0408	0.8427	-0.1823
15.7.2015	-0.0038	0.0038	-0.0834	0.0408	0.8427
16.7.2015	0.0007	0.0007	-0.4729	-0.0834	0.0408
20.7.2015	-0.0179	0.0179	0.8065	-0.2585	0.5819
21.7.2015	0.0032	0.0032	0.0690	0.8065	-0.2585
22.7.2015	-0.0044	0.0044	0.0488	0.0690	0.8065
23.7.2015	-0.0362	0.0362	0.1054	0.0488	0.0690
24.7.2015	0.0048	0.0048	-0.2782	0.1054	0.0488
27.7.2015	-0.0174	0.0174	0.3857	0.0390	-0.5691
28.7.2015	0.0087	0.0087	-0.0408	0.3857	0.0390
29.7.2015	0.0007	0.0007	0.2559	-0.0408	0.3857
30.7.2015	0.0025	0.0025	0.0924	0.2559	-0.0408
31.7.2015	0.0207	0.0207	-0.1942	0.0924	0.2559
3.8.2015	-0.0221	0.0221	0.5695	-0.2496	-0.3878
4.8.2015	0.0009	0.0009	0.1579	0.5695	-0.2496
5.8.2015	-0.0013	0.0013	-0.1192	0.1579	0.5695
6.8.2015	0.0085	0.0085	0.1414	-0.1192	0.1579
7.8.2015	-0.0048	0.0048	-0.1542	0.1414	-0.1192
10.8.2015	-0.0120	0.0120	0.8979	-0.0274	-0.7458
11.8.2015	0.0283	0.0283	0.0244	0.8979	-0.0274
12.8.2015	-0.0196	0.0196	-0.0244	0.0244	0.8979
13.8.2015	-0.0140	0.0140	0.0715	-0.0244	0.0244
14.8.2015	0.0029	0.0029	-0.1221	0.0715	-0.0244
17.8.2015	-0.0050	0.0050	0.7191	-0.3826	-0.3548
18.8.2015	-0.0126	0.0126	0.0741	0.7191	-0.3826
19.8.2015	-0.0087	0.0087	0.0235	0.0741	0.7191
20.8.2015	-0.0082	0.0082	-0.0476	0.0235	0.0741
21.8.2015	-0.0119	0.0119	0.0706	-0.0476	0.0235
24.8.2015	-0.0338	0.0338	0.8398	0.0985	-0.9808
25.8.2015	0.0299	0.0299	0.0225	0.8398	0.0985
26.8.2015	0.0014	0.0014	0.0000	0.0225	0.8398
27.8.2015	0.0161	0.0161	0.1054	0.0000	0.0225
28.8.2015	-0.0023	0.0023	-0.2107	0.1054	0.0000
31.8.2015	0.0076	0.0076	1.0176	-0.5000	-0.5443
1.9.2015	-0.0221	0.0221	0.1138	1.0176	-0.5000
2.9.2015	0.0012	0.0012	0.0317	0.1138	1.0176
3.9.2015	0.0047	0.0047	-0.1576	0.0317	0.1138
4.9.2015	-0.0143	0.0143	0.0706	-0.1576	0.0317
7.9.2015	-0.0150	0.0150	0.6627	0.1069	-0.7885
8.9.2015	0.0026	0.0026	-0.3552	0.6627	0.1069
9.9.2015	-0.0007	0.0007	0.2231	-0.3552	0.6627
10.9.2015	-0.0022	0.0022	-0.1252	0.2231	-0.3552
11.9.2015	-0.0069	0.0069	0.0770	-0.1252	0.2231
14.9.2015	-0.0007	0.0007	0.6592	-0.0017	-0.5026

15.9.2015	0.0259	0.0259	0.0339	0.6592	-0.0017
16.9.2015	0.0133	0.0133	0.0953	0.0339	0.6592
17.9.2015	0.0111	0.0111	-0.0625	0.0953	0.0339
18.9.2015	0.0016	0.0016	-0.1259	-0.0625	0.0953
21.9.2015	0.0101	0.0101	0.7376	-0.1204	-0.5781
22.9.2015	-0.0115	0.0115	-0.1273	0.7376	-0.1204
23.9.2015	-0.0051	0.0051	-0.4626	-0.1273	0.7376
28.9.2015	-0.0175	0.0175	1.0194	0.2863	-0.0645
29.9.2015	0.0128	0.0128	0.0000	1.0194	0.2863
30.9.2015	-0.0007	0.0007	0.0305	0.0000	1.0194
1.10.2015	0.0044	0.0044	-0.5276	0.0305	0.0000
2.10.2015	-0.0018	0.0018	0.1272	-0.5276	0.0305
5.10.2015	0.0331	0.0331	0.7329	0.2614	-0.7082
6.10.2015	0.0046	0.0046	0.0506	0.7329	0.2614
7.10.2015	0.0185	0.0185	0.1164	0.0506	0.7329
8.10.2015	-0.0005	0.0005	0.0741	0.1164	0.0506
9.10.2015	0.0070	0.0070	-0.2675	0.0741	0.1164
12.10.2015	0.0011	0.0011	0.8001	-0.0107	-0.7340
13.10.2015	-0.0119	0.0119	-0.0910	0.8001	-0.0107
14.10.2015	0.0130	0.0130	0.1876	-0.0910	0.8001
15.10.2015	-0.0015	0.0015	0.0131	0.1876	-0.0910
16.10.2015	-0.0099	0.0099	0.0629	0.0131	0.1876
19.10.2015	0.0158	0.0158	1.0253	-0.3662	-0.6690
20.10.2015	0.0095	0.0095	-0.0559	1.0253	-0.3662
21.10.2015	-0.0091	0.0091	-0.0965	-0.0559	1.0253
22.10.2015	0.0061	0.0061	0.0614	-0.0965	-0.0559
23.10.2015	-0.0016	0.0016	0.1744	0.0614	-0.0965
26.10.2015	-0.0108	0.0108	0.8473	0.1738	-1.0788
27.10.2015	-0.0076	0.0076	-0.1823	0.8473	0.1738
28.10.2015	-0.0016	0.0016	-0.0896	-0.1823	0.8473
30.10.2015	0.0111	0.0111	0.7949	-0.8267	-0.0896
2.11.2015	0.0526	0.0526	1.2040	0.0767	-0.5718
3.11.2015	-0.0094	0.0094	-0.2357	1.2040	0.0767
4.11.2015	0.0092	0.0092	-0.0520	-0.2357	1.2040
5.11.2015	-0.0087	0.0087	0.1014	-0.0520	-0.2357
6.11.2015	-0.0124	0.0124	-0.1284	0.1014	-0.0520
9.11.2015	0.0015	0.0015	0.7958	-0.0070	-0.6795
10.11.2015	-0.0107	0.0107	-0.0760	0.7958	-0.0070
11.11.2015	0.0067	0.0067	-0.0541	-0.0760	0.7958
12.11.2015	0.0052	0.0052	-0.1658	-0.0541	-0.0760
13.11.2015	-0.0032	0.0032	0.2586	-0.1658	-0.0541
16.11.2015	-0.0102	0.0102	0.6232	0.1857	-1.0022
17.11.2015	0.0013	0.0013	-0.0146	0.6232	0.1857
18.11.2015	-0.0079	0.0079	-0.0299	-0.0146	0.6232
19.11.2015	-0.0009	0.0009	0.0588	-0.0299	-0.0146
20.11.2015	0.0030	0.0030	-0.0438	0.0588	-0.0299

23.11.2015	-0.0117	0.0117	0.6802	0.0092	-0.5671
24.11.2015	-0.0449	0.0449	-0.1243	0.6802	0.0092
25.11.2015	0.0078	0.0078	-0.0148	-0.1243	0.6802
26.11.2015	-0.0242	0.0242	0.0294	-0.0148	-0.1243
27.11.2015	0.0085	0.0085	0.0700	0.0294	-0.0148
30.11.2015	-0.0054	0.0054	0.5528	0.1519	-0.7205
1.12.2015	0.0204	0.0204	0.0136	0.5528	0.1519
2.12.2015	-0.0051	0.0051	-0.1452	0.0136	0.5528
3.12.2015	-0.0124	0.0124	-0.0157	-0.1452	0.0136
4.12.2015	-0.0159	0.0159	0.0157	-0.0157	-0.1452
7.12.2015	-0.0048	0.0048	0.7404	-0.4345	-0.3977
8.12.2015	-0.0110	0.0110	0.2076	0.7404	-0.4345
9.12.2015	0.0201	0.0201	-0.0780	0.2076	0.7404
10.12.2015	-0.0303	0.0303	0.0654	-0.0780	0.2076
11.12.2015	-0.0291	0.0291	0.1192	0.0654	-0.0780
14.12.2015	-0.0139	0.0139	0.6931	-0.1494	-0.7044
15.12.2015	0.0403	0.0403	0.2019	0.6931	-0.1494
16.12.2015	0.0093	0.0093	-0.1138	0.2019	0.6931
17.12.2015	0.0120	0.0120	0.0120	-0.1138	0.2019
18.12.2015	-0.0171	0.0171	-0.1133	0.0120	-0.1138
21.12.2015	0.0119	0.0119	0.5534	0.1529	-0.6039
22.12.2015	-0.0031	0.0031	0.0953	0.5534	0.1529
23.12.2015	0.0128	0.0128	0.0000	0.0953	0.5534
24.12.2015	0.0001	0.0001	0.1278	0.0000	0.0953
25.12.2015	0.0019	0.0019	-0.0408	0.1278	0.0000
28.12.2015	0.0007	0.0007	0.8708	-0.2785	-0.6325
29.12.2015	-0.0045	0.0045	-0.0599	0.8708	-0.2785
30.12.2015	-0.0097	0.0097	-0.1898	-0.0599	0.8708
31.12.2015	-0.0203	0.0203	-0.2344	-0.1898	-0.0599
4.1.2016	-0.0170	0.0170	0.5423	0.0345	-0.3697
5.1.2016	0.0024	0.0024	0.1408	0.5423	0.0345
6.1.2016	0.0072	0.0072	0.0101	0.1408	0.5423
7.1.2016	0.0042	0.0042	-0.0726	0.0101	0.1408
8.1.2016	-0.0124	0.0124	-0.1888	-0.0726	0.0101
11.1.2016	0.0062	0.0062	1.1436	-0.2041	-0.8174
12.1.2016	0.0097	0.0097	0.0430	1.1436	-0.2041
13.1.2016	0.0107	0.0107	0.0105	0.0430	1.1436
14.1.2016	-0.0079	0.0079	-0.2877	0.0105	0.0430
15.1.2016	-0.0123	0.0123	0.0274	-0.2877	0.0105
18.1.2016	-0.0003	0.0003	1.0885	-0.2250	-0.5429
19.1.2016	0.0005	0.0005	-0.3223	1.0885	-0.2250
20.1.2016	-0.0209	0.0209	0.3425	-0.3223	1.0885
21.1.2016	-0.0150	0.0150	-0.1508	0.3425	-0.3223
22.1.2016	0.0241	0.0241	-0.1105	-0.1508	0.3425
25.1.2016	0.0042	0.0042	0.8664	0.0214	-0.7603
26.1.2016	0.0178	0.0178	-0.0114	0.8664	0.0214

27.1.2016	0.0034	0.0034	-0.1484	-0.0114	0.8664
28.1.2016	0.0052	0.0052	0.0263	-0.1484	-0.0114
29.1.2016	0.0144	0.0144	0.1888	0.0263	-0.1484
1.2.2016	-0.0005	0.0005	0.6466	-0.1280	-0.6825
2.2.2016	-0.0129	0.0129	-0.0488	0.6466	-0.1280
3.2.2016	0.0104	0.0104	0.0165	-0.0488	0.6466
4.2.2016	0.0168	0.0168	0.1376	0.0165	-0.0488
5.2.2016	-0.0041	0.0041	-0.0588	0.1376	0.0165
8.2.2016	-0.0301	0.0301	0.6665	-0.0627	-0.4761
9.2.2016	-0.0082	0.0082	-0.0994	0.6665	-0.0627
10.2.2016	0.0028	0.0028	-0.0616	-0.0994	0.6665
11.2.2016	-0.0094	0.0094	0.0157	-0.0616	-0.0994
12.2.2016	-0.0001	0.0001	0.1038	0.0157	-0.0616
15.2.2016	0.0010	0.0010	0.4940	0.2839	-0.9305
16.2.2016	-0.0008	0.0008	0.0968	0.4940	0.2839
17.2.2016	0.0258	0.0258	0.0153	0.0968	0.4940
18.2.2016	0.0088	0.0088	-0.0465	0.0153	0.0968
19.2.2016	-0.0059	0.0059	0.0616	-0.0465	0.0153
22.2.2016	0.0254	0.0254	0.8979	-0.0674	-0.6212
23.2.2016	0.0081	0.0081	0.2107	0.8979	-0.0674
24.2.2016	-0.0192	0.0192	-0.2107	0.2107	0.8979
25.2.2016	0.0152	0.0152	0.0244	-0.2107	0.2107
26.2.2016	-0.0036	0.0036	-0.0368	0.0244	-0.2107
29.2.2016	0.0117	0.0117	0.9232	-0.1277	-0.8557
1.3.2016	0.0019	0.0019	0.0916	0.9232	-0.1277
2.3.2016	0.0109	0.0109	0.0606	0.0916	0.9232
3.3.2016	0.0005	0.0005	-0.1942	0.0606	0.0916
4.3.2016	0.0047	0.0047	-0.0290	-0.1942	0.0606
7.3.2016	0.0038	0.0038	1.0986	-0.5581	-0.4818
8.3.2016	0.0026	0.0026	0.1273	1.0986	-0.5581
9.3.2016	0.0135	0.0135	-0.1151	0.1273	1.0986
10.3.2016	0.0036	0.0036	0.0706	-0.1151	0.1273
11.3.2016	0.0045	0.0045	-0.1869	0.0706	-0.1151
14.3.2016	0.0092	0.0092	0.7885	0.1139	-0.7641
15.3.2016	-0.0136	0.0136	-0.0953	0.7885	0.1139
16.3.2016	0.0043	0.0043	-0.0126	-0.0953	0.7885
17.3.2016	0.0250	0.0250	0.0849	-0.0126	-0.0953
18.3.2016	0.0191	0.0191	-0.0976	0.0849	-0.0126
21.3.2016	0.0055	0.0055	0.8014	-0.0688	-0.6431
22.3.2016	-0.0198	0.0198	-0.0526	0.8014	-0.0688
23.3.2016	-0.0171	0.0171	0.0526	-0.0526	0.8014
24.3.2016	0.0121	0.0121	0.0741	0.0526	-0.0526
25.3.2016	0.0000	0.0000	-0.0488	0.0741	0.0526
28.3.2016	-0.0001	0.0001	1.0217	0.0207	-0.7711
29.3.2016	0.0048	0.0048	-0.0834	1.0217	0.0207
30.3.2016	0.0144	0.0144	-0.0559	-0.0834	1.0217

31.3.2016	0.0042	0.0042	0.1088	-0.0559	-0.0834
1.4.2016	-0.0110	0.0110	-0.1680	0.1088	-0.0559
4.4.2016	0.0182	0.0182	0.8190	0.0016	-0.6690
5.4.2016	-0.0109	0.0109	-0.0328	0.8190	0.0016
6.4.2016	-0.0177	0.0177	-0.1178	-0.0328	0.8190
7.4.2016	-0.0043	0.0043	-0.0382	-0.1178	-0.0328
8.4.2016	0.0163	0.0163	0.0506	-0.0382	-0.1178
11.4.2016	0.0178	0.0178	0.8508	0.0578	-0.7569
12.4.2016	-0.0032	0.0032	-0.1100	0.8508	0.0578
13.4.2016	0.0233	0.0233	0.1508	-0.1100	0.8508
14.4.2016	0.0010	0.0010	-0.1625	0.1508	-0.1100
15.4.2016	-0.0025	0.0025	-0.0359	-0.1625	0.1508
18.4.2016	0.0090	0.0090	1.1093	-0.3375	-0.6690
19.4.2016	-0.0011	0.0011	-0.1125	1.1093	-0.3375
20.4.2016	-0.0082	0.0082	0.1335	-0.1125	1.1093
21.4.2016	0.0014	0.0014	-0.1576	0.1335	-0.1125
22.4.2016	0.0018	0.0018	0.0476	-0.1576	0.1335
25.4.2016	-0.0084	0.0084	0.7958	-0.0570	-0.8168
26.4.2016	0.0076	0.0076	-0.0629	0.7958	-0.0570
27.4.2016	-0.0045	0.0045	0.0256	-0.0629	0.7958
28.4.2016	0.0012	0.0012	-0.0520	0.0256	-0.0629
29.4.2016	-0.0018	0.0018	0.1133	-0.0520	0.0256
2.5.2016	-0.0177	0.0177	0.8518	-0.0616	-0.8473
3.5.2016	-0.0335	0.0335	0.1014	0.8518	-0.0616
4.5.2016	-0.0210	0.0210	-0.1148	0.1014	0.8518
5.5.2016	-0.0087	0.0087	0.0654	-0.1148	0.1014
6.5.2016	-0.0042	0.0042	-0.0790	0.0654	-0.1148
9.5.2016	0.0088	0.0088	0.9416	0.0148	-0.7069
10.5.2016	-0.0033	0.0033	-0.0943	0.9416	0.0148
11.5.2016	0.0029	0.0029	-0.0565	-0.0943	0.9416
12.5.2016	-0.0092	0.0092	-0.0117	-0.0565	-0.0943
13.5.2016	-0.0064	0.0064	-0.0988	-0.0117	-0.0565
16.5.2016	-0.0104	0.0104	0.9395	0.2083	-0.9765
17.5.2016	0.0036	0.0036	-0.2032	0.9395	0.2083
18.5.2016	-0.0004	0.0004	0.1068	-0.2032	0.9395
20.5.2016	-0.0115	0.0115	0.9163	-1.0372	0.1068
23.5.2016	0.0053	0.0053	0.9708	-0.0456	-0.9163
24.5.2016	0.0342	0.0342	0.2763	0.9708	-0.0456
25.5.2016	-0.0104	0.0104	-0.0715	0.2763	0.9708
26.5.2016	-0.0073	0.0073	0.0123	-0.0715	0.2763
27.5.2016	-0.0001	0.0001	-0.1027	0.0123	-0.0715
30.5.2016	0.0065	0.0065	0.7641	-0.1895	-0.7205
31.5.2016	-0.0094	0.0094	-0.0138	0.7641	-0.1895
1.6.2016	-0.0099	0.0099	0.0800	-0.0138	0.7641
2.6.2016	-0.0100	0.0100	0.1542	0.0800	-0.0138
3.6.2016	0.0242	0.0242	-0.1934	0.1542	0.0800

6.6.2016	0.0058	0.0058	0.7754	-0.2731	-0.5798
7.6.2016	-0.0056	0.0056	0.1119	0.7754	-0.2731
8.6.2016	0.0086	0.0086	0.0117	0.1119	0.7754
9.6.2016	-0.0143	0.0143	-0.0355	0.0117	0.1119
10.6.2016	-0.0107	0.0107	0.0585	-0.0355	0.0117
13.6.2016	-0.0046	0.0046	0.8755	-0.0508	-0.8398
14.6.2016	-0.0102	0.0102	-0.0120	0.8755	-0.0508
15.6.2016	0.0063	0.0063	-0.0244	-0.0120	0.8755
16.6.2016	-0.0208	0.0208	-0.0250	-0.0244	-0.0120
17.6.2016	0.0101	0.0101	-0.0928	-0.0250	-0.0244
20.6.2016	0.0274	0.0274	0.8303	-0.1052	-0.7802
21.6.2016	0.0001	0.0001	-0.0662	0.8303	-0.1052
22.6.2016	-0.0034	0.0034	0.1284	-0.0662	0.8303
23.6.2016	0.0093	0.0093	0.0698	0.1284	-0.0662
24.6.2016	-0.0342	0.0342	-0.0343	0.0698	0.1284
27.6.2016	-0.0027	0.0027	0.8664	0.2212	-1.0204
28.6.2016	0.0233	0.0233	-0.1079	0.8664	0.2212
29.6.2016	-0.0028	0.0028	0.2357	-0.1079	0.8664
30.6.2016	0.0014	0.0014	-0.1054	0.2357	-0.1079
1.7.2016	0.0147	0.0147	0.0220	-0.1054	0.2357
4.7.2016	0.0056	0.0056	0.6554	-0.2751	-0.9664
8.7.2016	-0.0047	0.0047	0.8313	0.0377	-0.1431
11.7.2016	0.0155	0.0155	1.0415	0.3559	-1.0826
12.7.2016	0.0238	0.0238	0.1112	1.0415	0.3559
13.7.2016	0.0022	0.0022	-0.0765	0.1112	1.0415
14.7.2016	0.0155	0.0155	0.0974	-0.0765	0.1112
15.7.2016	0.0028	0.0028	-0.2180	0.0974	-0.0765
18.7.2016	-0.0735	0.0735	0.9676	0.0576	-0.7458
19.7.2016	-0.0102	0.0102	-0.1165	0.9676	0.0576
20.7.2016	-0.0169	0.0169	-0.1982	-0.1165	0.9676
21.7.2016	-0.0452	0.0452	0.2528	-0.1982	-0.1165
22.7.2016	0.0020	0.0020	-0.1995	0.2528	-0.1982
25.7.2016	0.0334	0.0334	1.1087	0.0374	-0.8473
26.7.2016	-0.0066	0.0066	-0.1863	1.1087	0.0374
27.7.2016	0.0186	0.0186	-0.0244	-0.1863	1.1087
28.7.2016	0.0022	0.0022	0.1803	-0.0244	-0.1863
29.7.2016	0.0021	0.0021	-0.1204	0.1803	-0.0244
1.8.2016	0.0172	0.0172	0.9765	-0.0245	-0.9578
2.8.2016	-0.0119	0.0119	0.0000	0.9765	-0.0245
3.8.2016	-0.0167	0.0167	-0.0263	0.0000	0.9765
4.8.2016	0.0209	0.0209	0.0132	-0.0263	0.0000
5.8.2016	-0.0008	0.0008	-0.1112	0.0132	-0.0263
8.8.2016	0.0223	0.0223	0.7732	0.1657	-0.9237
9.8.2016	0.0095	0.0095	0.1542	0.7732	0.1657
10.8.2016	-0.0073	0.0073	-0.1041	0.1542	0.7732
11.8.2016	0.0137	0.0137	0.0706	-0.1041	0.1542

12.8.2016	-0.0102	0.0102	-0.0706	0.0706	-0.1041
15.8.2016	0.0031	0.0031	1.1394	-0.1486	-0.7958
16.8.2016	-0.0098	0.0098	-0.2485	1.1394	-0.1486
17.8.2016	0.0057	0.0057	-0.0129	-0.2485	1.1394
18.8.2016	-0.0023	0.0023	0.0382	-0.0129	-0.2485
19.8.2016	0.0022	0.0022	-0.1054	0.0382	-0.0129
22.8.2016	-0.0025	0.0025	0.9094	-0.2871	-0.6391
23.8.2016	-0.0080	0.0080	0.0541	0.9094	-0.2871
24.8.2016	-0.0159	0.0159	-0.1411	0.0541	0.9094
25.8.2016	0.0088	0.0088	0.1278	-0.1411	0.0541
26.8.2016	0.0043	0.0043	-0.0134	0.1278	-0.1411
29.8.2016	-0.0131	0.0131	0.9765	-0.2260	-0.7205
31.8.2016	-0.0020	0.0020	0.7754	-0.7885	0.9765
1.9.2016	-0.0015	0.0015	0.0513	0.7754	-0.7885
2.9.2016	0.0135	0.0135	0.0124	0.0513	0.7754
5.9.2016	0.0117	0.0117	0.6931	0.1907	-0.8391
6.9.2016	0.0026	0.0026	-0.1911	0.6931	0.1907
7.9.2016	-0.0045	0.0045	0.0387	-0.1911	0.6931
8.9.2016	0.0026	0.0026	-0.0928	0.0387	-0.1911
9.9.2016	-0.0102	0.0102	-0.0720	-0.0928	0.0387
16.9.2016	-0.0135	0.0135	0.9754	-0.3302	0.2469
19.9.2016	0.0215	0.0215	1.0116	-0.0844	-0.7097
20.9.2016	-0.0046	0.0046	0.0129	1.0116	-0.0844
21.9.2016	0.0078	0.0078	0.0377	0.0129	1.0116
22.9.2016	0.0238	0.0238	0.0244	0.0377	0.0129
23.9.2016	-0.0005	0.0005	-0.0121	0.0244	0.0377
26.9.2016	-0.0387	0.0387	0.9676	0.0876	-0.9102
27.9.2016	0.0057	0.0057	-0.2485	0.9676	0.0876
28.9.2016	0.0067	0.0067	0.1206	-0.2485	0.9676
29.9.2016	-0.0078	0.0078	0.0000	0.1206	-0.2485
30.9.2016	-0.0077	0.0077	0.0553	0.0000	0.1206
3.10.2016	0.0096	0.0096	0.9664	-0.1792	-0.7714
4.10.2016	-0.0022	0.0022	0.0000	0.9664	-0.1792
5.10.2016	0.0103	0.0103	-0.0220	0.0000	0.9664
6.10.2016	0.0005	0.0005	-0.0339	-0.0220	0.0000
7.10.2016	0.0010	0.0010	-0.0116	-0.0339	-0.0220
10.10.2016	-0.0018	0.0018	0.8082	-0.0463	-0.7167
11.10.2016	-0.0025	0.0025	-0.0220	0.8082	-0.0463
12.10.2016	-0.0024	0.0024	0.1054	-0.0220	0.8082
13.10.2016	-0.0084	0.0084	0.0000	0.1054	-0.0220
14.10.2016	0.0096	0.0096	-0.0619	0.0000	0.1054
17.10.2016	-0.0015	0.0015	0.9163	-0.1342	-0.8797
18.10.2016	0.0116	0.0116	0.0347	0.9163	-0.1342
19.10.2016	0.0110	0.0110	-0.0347	0.0347	0.9163
20.10.2016	0.0005	0.0005	0.0117	-0.0347	0.0347
21.10.2016	-0.0052	0.0052	0.0783	0.0117	-0.0347

24.10.2016	0.0137	0.0137	0.8815	-0.0169	-0.7714
25.10.2016	-0.0063	0.0063	-0.0518	0.8815	-0.0169
26.10.2016	-0.0004	0.0004	-0.0324	-0.0518	0.8815
27.10.2016	-0.0083	0.0083	-0.0920	-0.0324	-0.0518
28.10.2016	-0.0052	0.0052	-0.1014	-0.0920	-0.0324