ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

GOOGLE SEARCH AND STOCK RETURNS: A STUDY ON BIST 100 STOCKS

M.Sc. THESIS

Ali Eray BULUT

Department of Management Engineering

Management Engineering Programme

JUNE 2018

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

GOOGLE ARAMALARI VE HİSSE GETİRİLERİ: BIST 100 HİSSELERİ ÜZERİNE BİR ÇALIŞMA

YÜKSEK LİSANS TEZİ

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Ali Eray Bulut, a **M.Sc.** student of ITU **Graduate School of Science Engineering and Technology** student ID **507151002**, successfully defended the **thesis** entitled "**GOOGLE SEARCH AND STOCK RETURNS: A STUDY ON BIST 100 STOCKS**", which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Doç. Dr. Cumhur EKİNCİ** İstanbul Technical University	....
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	Prof. Dr. Suat TEKER Işık University	....

To my family,

FOREWORD

I am grateful to my advisor Doç. Dr. Cumhur Ekinci for his guidance and support. I would also like to thank my family members for their encouragement throughout my education life.

June 2018

Ali Eray Bulut
(Civil Engineer)

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ABBREVIATIONS

BE/ME	**:** Book to Market Equity
CAPM	**:** Capital Asset Pricing Model
E/P	**:** Earnings Price Ratio
EMH	**:** Efficient Market Hypothesis
HML	**:** High Minus Low
MRP	**:** Market Risk Premium
OLS	**:** Ordinary Least Squares
Rf	**:** Risk Free Rate
Rm	**:** Market Return
SMB	**:** Small Minus Big
SML	**:** Security Market Line
SV	**:** Google Search Volume

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GOOGLE SEARCH AND STOCK RETURNS: A STUDY ON BIST 100 STOCKS

ABSTRACT

With the propagation of internet and increase in its usage, people started to use internet for everything in their lives. This leads to creation of huge amount of data and gives huge opportunitiy to researchers to gain insights into behavior of people. Being one of the most visited and used websites, Google is naturally one of the most appealing sources of data. Fortunately, Google Trends shares Google search volume regularly. Google Trends has been exploited by researchers in the recent years and one of the areas that researchers benefit from Google search volume is investor attention.

Some scholars employed Google Trends to study the relationship between Google search volume and stock returns. There are already some proxies such as extreme returns, trading volume, and news. Though, they each have a number of flaws in representing the investor attention. Google search volume, on the other hand, is found effective in representing investor attention by some researchers. A few scholars determined that there is a temporary increase in stock returns following an increase in investor attention, which is referred to as price pressure caused by uninformed individual investors in the literature.

Existence of this relationship would also challenge the Efficient Market Hypothesis which implies that stocks should reflect all available information and it is not possible to beat the market. If this relationship is proved, then it would be possible to beat the market by investing in most searched stocks.

This thesis examines existence of the relationship between Google search and stock returns in Turkish stock market. To capture this relationship, first, separate OLS regressions for BIST 100 stocks are performed and examined whether search volume has explanatory power in stock returns. It is studied whether search volume is associated with return increases or decreases. In the second part of the analysis, stocks are sorted into four portfolios based on their search volumes. If there really is a relationship between Google search and stock returns, then portfolio of the most searched stocks should generate the most abnormal returns. In both of the analyses Fama French three factor model is used. In addition to the literature, direction of the relationship is also examined. Because, it could be the ncrease investor attention that precedes increase in returns or high stock returns may be attracting the attention of investors and cause the internet search volume to increase.

The results show that there is a linkage between Google search volume and stock returns but direction of this relationship is somewhat vague. There is a positive and significant relationship for searches made at time t. However, this does not guarantee that the direction is from internet search to stock returns, because it is not clear on which day of the week search interest and returns start to increase. It is also possible that people start to buy the stocks after being aware of the extreme returns. On the other hand, the relationship is also positive and significant for searches made at time

t+1, which implies that the direction may be from stock returns to internet search. After realizing that a particular stock's return has increased drastically recently, investors search for these stocks on Google which causes the high search volume and the relationship. This result actually shows the efficiency of Turkish market. Further research with daily data can enhance results of this study by revealing the direction of the relationship. This can make an explanation to the significant result at time t.

GOOGLE ARAMALARI VE HİSSE GETİRİLERİ: BİST 100 HİSSELERİ ÜZERİNE BİR ÇALIŞMA

ÖZET

Son yıllarda internetin yayılması ve kullanım oranlarının artmasıyla artık insanlar her konuda internetten yaralanmaya başlamışlardır. Dolayısıyla, internet insanların zihinlerindeki düşüncelerin yansıması haline gelmiştir. İnsanların ilgilerini anlamaya olanak sağlaması internet verisini araştırmacılar için ilgi çekici hale getirmiştir.

Google da en çok kullanılan arama motorlarının ve en çok kullanılan internet sitelerinin başında gelmektedir. Her türlü bilgi talebine vesile olması Google'ı önemli bir veri kaynağı yapmaktadır. Neyse ki, Google arama istatistiklerini Google Trends internet sitesinde düzenli olarak paylaşmaktadır. Araştırmacılar bu veriden sağlıktan ekonomiye birçok alanda faydalanmaktadır.

Google arama hacmi verisi finans alanında da kullanılmaya başlanmıştır ve en çok kullanılan alanlardan birisi yatırımcı ilgisi olmuştur. Bazı araştırmacılar Google arama hacminin hisse getirileriyle ilişkili olabileceğini öne sürmüşlerdir. Google aramalarının hisseye olan ilgiyi gösterdiği ve alımların öncülü olduğu ortaya konmuştur.

Google aramaları ve hisse fiyatı ilişkisi aynı zamanda Etkin Piyasa Hipotezi'nin aksini ispatlamak anlamına gelecektir. Etkin Piyasa Hipotezi, piyasanın tüm mevcut bilgileri fiyatlayacağını ve piyasayı yenmenin mümkün olmadığını söylemektedir. Eğer bu ilişki ispatlanırsa bu durumda, fazla aranan şirketlere yatırım yaparak getiri elde etmek mümkün olacaktır.

Aslında Google aramaları dışında yatırımcı ilgisini yansıtan yüksek getiri, işlem hacmi, haberler gibi bir takım göstergeler mevcuttur. Ama bunların çoğunlukla yatırımcı ilgisini tam anlamıyla göstermekte yetersiz kaldıkları yapılan çalışmalarda gösterilmiştir. Araştırmacılar alternatif olarak Google aramalarını kullanıp daha iyi sonuçlar verdiğini göstermişlerdir.

İnternet aramaları ve hisse getirisi ilişkisinin ispatlanması şu anlama gelmektedir: eğer arama hacmi artan şirketler sistematik bir şekilde getiri sağlıyorsa, bu hisselere yatırım yapmak mantıklı olacaktır. Yapılan bazı çalışmalarda Google aramalarının artmasından sonra hisse getirilerinde geçici bir artış gözlenmiştir. Genel olarak, bireysel yatırımcıların sebep olduğu bu duruma fiyat baskısı denmektedir. Yapılan çalışmaların bir kısmında Google aralamalarındaki artışın ardında getirilerde geçici bir artış olduğu gösterilmiştir. Bazı diğer çalışmalarda ise Google aramaları ile getiler arasında zayıf ilişki olduğu bulunmuştur. Yaptığım çalışma bu ilişkinin Türkiye'de olup olmadığını araştırmaktadır.

Bu çalışmada kullanılan hisselerin Google arama hacmi verisi Google Trends'den alınmıştır. Google arama hacim verisinin en önemli özelliği mutlak değil, göreli olmasıdır. Örneğin, bir sözcüğün belirli bir zaman dilimindeki arama hacim verisi elde

edilmek istendiğinde, sözcüğün bu zaman dilimi içerisinde en fazla arandığı güne 100 değeri verilmekte, bu en çok aramanın yapıldığı güne göre bağıl olarak 0 dan 100'e değerler almaktadır. Burada dikkat edilmesi gereken bir diğer husus ise anahtar sözcük seçimidir. Anahtar sözcük olarak hisselerin ismi kullanıldığında hisse araştırmasından daha farklı amaçlarla yapılan aramalar da dahil edilmiş olmaktadır. Örneğin, sadece hisselere değil, aynı zamanda şirketin ürettiği ürünlere yönelik olan aramalar da dahil edilmektedir. Bu sorun, yapılan bazı çalışmalarda hisselerin borsa kodları kullanılarak aşılmıştır. Böylelikle sadece hisse ile ilgili aramalar göz önüne alınmaktadır.

Hisse getirilerinin hesabında Fama French Üç Faktör Modeli kullanılmıştır. Fama French Üç Faktör Modeli hisse getirilerini açıklamak için piyasa risk priminin yanı sıra SMB (small minus big - küçük eksi büyük), HML (high minus low - yüksek eksi düşük) faktörlerini kullanmaktadır. SMB faktörü küçük ve büyük hisseler arasındaki getiri farkını göstermekte, HML ise yüksek ve düşük defter değeri/piyasa değeri oranına sahip hisseler arasındaki getiri farkını temsil etmektedir.

Çalışmamda Google aramalarıyla hisse getirileri ilişkisi iki farklı yöntemle araştırılmıştır. İlk yöntem olarak BIST 100 hisseleri için ayrı ayrı regresyonlar yapılmıştır. Google aramalarının hisse getirilerinde açıklayıcı etkisinin olup olmadığı araştırılmıştır. Google aramalarının Fama French Üç Faktör Modeli'ne ek olarak açıklayıcı değişken şeklinde eklendiğinde anlamlı olup olmadığı araştırılmıştır. Regresyon sonuçlarında arama hacmi katsayılarının anlamlı olması, Google aramaları ve hisse getirilerinin gerçekten de ilişkili olduğunu gösterecektir. Google aramalarının katsayılarının sadece anlamlı olup olmadığı değil, aynı zamanda pozitif mi negatif mi olduğu da araştırılmıştır. Böylelikle, Google aramalarının hisse getirilerindeki artış ile mi düşüş ile mi ilişkili olduğu ve fiyat baskısını destekleyip desteklemediği ortaya çıkacaktır.

İkinci bir yöntem olarak da literatüre uygun olarak hisseler arama hacimlerine göre gruplandırılmıştır. En çok aranan şirketlerin getirileri ve en az aranan şirketlerin getirileri hesaplanmıştır. Sonuç olarak, en çok aranan hisselerden oluşan grubun en yüksek getiriyi sağlaması ve sabit katsayısının anlamlı olması ve en az aranan şirketlerin de en az getiriyi sağlaması aynı şekilde Google aramaları ve hisse getirilerinin gerçekten de ilişkili olduğuna işaret edecektir. İki yöntemde de Fama French Üç Faktör Modeli kullanılmıştır.

Google arama hacim verisinin özellikleri nedeniyle ortaya çıkabilecek birtakım sorunları ortadan kaldırabilmek adına arama hacim verisi literatüre uygun olarak üç farklı yöntemle kullanılmıştır.

Mevcut literatüre ek olarak, Google aramaları ve hisse getirileri arasındaki ilişkinin yönü de saptanmaya çalışılmıştır. Çünkü, ilişkili olmaları hangisinin daha önce arttığı hakkında bilgi vermeyebilir. Yatırımcı ilgisindeki artıştan sonra getirilerin artabileceği gibi, getirilerdeki artış da yatırımcıların ilgisini ve dolayısıyla Google aramalarını artırabilir. Bu şekilde Google aramalarının hisse getirilerinin öncülü olup olmadığı net bir şekilde anlaşılacaktır.

Analizlerin sonucunda Google aramalarının hisse getirileriyle arasında bir ilişki bulunmuştur. Ancak, ilişkinin yönü net değildir. T anında yapılan aramalar ile hisse getirileri arasında kuvvetli bir ilişki vardır, ancak bu sonuç, ilişkinin yönünün Google aramalarından hisse getirilerine olduğu anlamına gelmemektedir, çünkü haftanın hangi günü aramaların arttığı ve hangi günü getirilerin arttığı bilinmemektedir. Eğer internet aramaları getirilerden daha önce arttıysa, bu, fiyat baskısına işaret eder ve literatürü doğrular. Ancak, eğer önce getiriler artar, sonra internet arama hacmi artarsa, bu sonuç fiyat baskısı hipotezini doğrulamaz.

Öte yandan, t+1 anında yapılan aramalar ile hisse getirileri arasında da kuvvetli ilişki olduğu saptanmıştır. Bu sonuç ilişkinin yönünün yüksek getirilerden internet aramalarına olabileceği anlamına gelmektedir, yani yüksek getiri sağlayan şirketler yatırımcıların ilgisini çekip Google'da aranmalarına sebep olmaktadır. Öte yandan, günlük verilerle yapılacak bir çalışma t anındaki ilişkinin yönünü açıklığa kavuşturacağından faydalı olacaktır.

Bu sonuçlar aynı zamanda Türkiye piyasasının etkinliğini göstermektedir. Çünkü, çok aranan hisselere yatırım yapmanın getiri sağlamayacağı görülmüştür ve bu Etkin Piyasa Hipotezini doğrulamaktadır.

1. INTRODUCTION

Recent advancements in technology offer many opportunities to scholars and internet is of course the most important ones. According to International Telecommunications Union, 48% of world population is using internet, while the ratio is much higher for developed coutries with 81% (URL1). People use it for everything in their lives, in any moment. To gather product information, to make academic research, for social networking or for just gathering information out of curiosity. Therefore, it basically reflects what is in people’s minds, which makes it such an appealing source of data.

Internet search, especially Google, has been used in academic literature very often in the recent years. One of the most commonly used areas is economic research. Various researchers employed Google search data for unemployment prediction, while others tried to forecast some economic indicators such as automobile sales, consumer confidence, travel destination planning, and unemployment. Google Trends also has many applications in health research. Notable amount of research were made about flu-related disaese prediction.

However, in recent years, it has also been used in finance literature. A number of scholars tried to benefit from internet data to gain insight into investor behavior. Investor attention is one of those areas of reasearch. Researchers tried to make use of internet search data to predict stock price movements, thinking that investors may buy a stock upon searching it on internet, which is also the aim of this study.

Scholars who studied the relationship of Google search volume and stock returns and found that an increase in Google search volume is followed by a temporary increase in returns that reverts in the long run, which is called price pressure. Most of the researchers who studied the topic found a significant relationship between Google search and stock returns and confirmed the existence of price pressure, while there are also a few studies which found a weak relationship.

Proof of the relationship between internet search and stock returns would challenge Efficient Market Hypothesis (EMH). EMH implies that stock prices reflect all possible information, and this means that it is not possible to beat the market. However, if this relationship is confirmed, traders can lock in considerable profits by monitoring search volumes of stocks.

This study aims to analyze the relationship between Google search volume and stock returns. There are some studies for different markets in the world. Majority of these studies report that there is a temporary increase in returns of stocks following an increase in Google search volume. There are also a few studies that found weak relationship or reverse relationship that foresees a decrease in returns after an increase in Google search volume. However, direction of this relationship is rarely examined. Thus, in this study it is also aimed to show the direction of the relationship, that is, whether increased search interest results in an increase in stock returns, or increase in stock returns attracts attention. Moreover, the relationship between internet search and stock returns is rarely examined for Turkish stock market. This study is aims to reveal the characteristics of Turkish investors.

In this study, first, Fama French three factor model will be explained. Second section covers features of Google Trends and related research. In the third section, literature about the relationship between Google search and stock returns is reviewed, data and methodology of the study will be explained, and analysis and results of the study will be presented and discussed. Last section includes the conluding remarks.

2. FAMA FRENCH THREE FACTOR MODEL

Fama French three factor model is one of the most fundamental methods of stock pricing. It was introduced by Fama and French in 1993. There were already some models such as CAPM, but they had some disadvantages. They came short in explaining some factors that affect stock prices, which led to development of a more sophisticated model that would make up for these risk factors, Fama-French three factor model.

2.1 Capital Asset Pricing Model (CAPM)

One of the most basic asset pricing models is Capital Asset Pricing Model (CAPM) in **(2.1)**. It was introduced by Sharpe (1964) and Lintner (1965). It is basically used to find the required rate of return for a particular stock.

$$R_i = R_f + \beta_i\left(E[R_m] - R_f\right) \tag{2.1}$$

Risky stocks have to offer greater returns in order to attract investors. If a risky stock offers the same return as a less risky stock, investors would of course choose the less risky stock. To capture how much return a stock has to offer, CAPM reflects the time value of money and a risk premium of holding that stock. The time value is captured by the risk free rate in the equation, while the risk premium is calculated by the beta of the stock multiplied by market risk premium. Market risk premium (MRP) is calculated as expected market return ($E[R_m]$) minus risk free rate (R_f), while beta (β_i) is the volatility of a stock. Expected market return ($E[R_m]$) is calculated from market's historical return data. β_i is the indicator of stock's performance against the market, and it is also calculated from the stock's past performance. If the stock performed in the same direction with the overall market in the past, it should have the same sign with the market. That is, if the stock typically showed an increase when the market increased, then its' sign must also be positive. On the other hand, if the stock typically increased by the same percentage with the market in the past, its' beta should be close to β_m. With the same logic, if the market typically showed an increase by some percentage and the stock typically showed and increase more than the market, we say that the stocks beta should be greater than one.

A stock has to offer a return that is at least equal to the required return, that is, CAPM. If a stock offers a return that is lower than what is implied by CAPM, it means that the stock is overvalued and it is not desirable. However, if a stock offers a return which is greater than what is implied by CAPM, it means that the stock is undervalued and it is more desirable. This is illustrated by the security market line (SML). Stocks over the line are the ones that offer greater return than required rate of return. These stocks are undervalued. And the stocks below the security market line are the ones that offer less return than required rate of return. These stocks are overvalued. Required rate of return increases as the volatility (β) increases.

2.2 Fama French Three Factor Model

In CAPM the idea is that β_i (E[R_m] - R_f) term captures the cross section of returns. However, many scholars prove that there are also some other factors that affect stock returns. Banz (1981) shows that market capitalization is another explanatory variable and states that it should be added to the CAPM equation. Bhandari (1988), on the other hand, finds that leverage is also relevant for stock returns. Stattman (1980), and Rosenberg et al. (1985) prove that book to market equity ratio (BE/ME) effects stock returns. Lakonishok (1991) shows that book to market equity has strong explanatory power in stock returns of Japanese stocks. Basu (1983) shows that earnings price (E/P) ratio also affects average returns of US stocks along with size and market beta. Ball (1978) asserts that E/P is compensates for all unnamed risk factors and that E/P is higher for riskier stocks. Fama and French (1992a), find that either alone or when used with other variables such as market capitalization, E/P, BE/ME, and leverage, β has no effect in explaining average stock returns. This is in line with the studies of Reinganum (1981) and Lakonishok and Shapiro (1986). However, market capitalization, earnings to price ratio, book to market equity, and leverage are all found to affect average stock returns when used alone. When combined, however, market capitalization and book to market equity seem to absorb the effects of leverage and E/P ratio. While both of them have explanatory power, effect of book to market equity is even stronger than the effect of market capitalization. Hence, Fama-French three factor model in **(2.2)** is more developed model and proved better in explaining stock returns.

$$R_{i,t} - R_{f,t} = \alpha + \beta_1(R_{m,t} - R_f) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{Qk,t} \qquad (2.2)$$

In the Fama and French three factor model, the first addition is about the market capitalization (market cap). Small market cap stocks are more volatile than the large market cap stocks. Small cap stocks for example can decrease drastically if a negative event happens (such as a news that affects product sales, or losing a client). They also rise in great percentage, when a good event happens such as a new contract with a profitable customer. Since they are riskier, they should compensate for this, which is indicated by SMB factor on the equation. Large cap stocks, on the other hand, do not respond bad events that much and do not decrease dramatically. Same way a positive event does not increase stock price much. So, they can be seen as more stable investments. Another important factor is price (or market) to book ratio (P/B). Stocks with high P/B ratios are those which increased market value of its' equity in the market, so that it would be above its' book value. Stocks with low P/B ratios are those which are traded below their potential, and thus can offer significant profits while returning to its' potential value. These are called value stocks. Value stocks outperform stocks with high P/B ratios and this needs to be accounted for in the pricing model by adding HML.

2.3 Followers of Three Factor Model

There are but some critiques to Fama French three factor model as well. Carhart (1997) shows that momentum is also a factor that affects stock returns. He makes three conclusions from his study. First, he states that funds that constantly perform bad should be avoided. He then points out that funds with high performance last year are likely to perform good also this year, but this does not continue afterwards. The last implication is that transaction costs and other related expenditures affect the fund performance negatively.

Fama and French (2015) state that these studies all show that Fama French three factor model overlooks the effect of invesment and profitability and show the necessity of a model that would also cover them. To prove the significance of these factors, they analyze seven different models. While Rm-Rf and SMB always remain in the model, they replace HML with RMW and CMA, respectively, to obtain three different models. Then, while again Rm-Rf and SMB always remain in the model they pick two factors out of three (HML, RMW, CMA), respectively, to obtain again four different four factor models. They, then analyze five factor model that includes both Rm-Rf, SMB, HML, RMW and CMA. They point out that five factor model comes short in seizing the low average return of small cap stocks who typically have low profitability but invest too much. They also find that the five factor model explains average returns better than the three factor model. However, they also find that four factor model that includes Rm-Rf, SMB, RMW and CMA is also very successful in explaining average returns so that it makes HML in the five factor redundant. This means that the five factor model is no better than the four factor model that includes Rm-Rf, SMB, RMW and CMA. It looks like effect of HML is absorbed by other factors, mainly RMW and CMA.

3. GOOGLE TRENDS

3.1 Functions of Google Trends

With the prevalence of internet, internet has become one of the most important sources of data and Google is of course of the most important ones. People use Google for all their needs, they use it for finding out ways of transportation, where to eat, which product to buy, where to spend their holidays, which movie to watch, not to mention how students and scholars benefit from it for their courses and research. Google Trends shares google search volume for many kinds of queries from many countries since 2004. It represents the search interest of population about any kind of topic. This opens up a huge opportunity for researchers and businesses and significant number of scholars try to benefit from this enormous source of data.

There are a few features in Google Trends which contribute to the robustness of search results. First of all, searches can be limited to country, state, or city. If the search volume is limited to a specific country, then searches made for that keyword from other countries in the world are excluded. The second feature is custom time range. With this feature it is possible to set a specific time range, provided that it starts after 2004. Search volumes can be obtained in hourly, daily, weekly or monthly frequencies depending on the time range. It also enables users to narrow the search by topics such as shopping, communities, news, internet and telecommunications, carriers and education, books and literature, entertainment, sports, health and travel. There are also subcategories of these general categories. For example, travel category is divided into subtopics such as air travel, road transport, rail transport, car rental, travel agencies, and touristic places. This way, only the searches relevant to the intended topic can be obtained and complexities that may arise due to common meanings are avoided. Another option that Google Trends gives is that Google Image search data, Google News search data, Google Shopping search data, Youtube search data can also be downloaded as well as the generalized Google search data.

These are actually features of Google that are not that frequently used, and appear as separate sheets in Google results page. With the image search feature it is possible to post an image and find out what, who or where it is. With the news search data number of searches for news can be obtained, which can be useful in many areas along with finance. With the shopping search tool number of searches for particular products can be obtained. Shopping search volumes can be applicable for various topics such as sales and marketing. Therefore, it is a very important feature. Youtube search volumes are also functional in many areas.

3.2 Google Search Volume Data and Its Features

Understanding Google Trends's working mechanism is crucial to the robustness of the study. First of all, the data that is drawn from google trends is not absolute, but relative so that when you want to obtain the search interest for a particular time range (i.e. from May 2016 to September 2017), the day with the highest absolute searches in the interval gets the score 100 and the remaining days are graded relatively. A day with 50 score means that day was half as popular as the day with 100 score, while the day with 0 score means that amount of searches in that day was 1% of the day with 100 score. As a result, searches with ignorable volume are excluded in the results.

Another feature is that, if a greater data is drawn which includes the same interval but is greater than it such as January 2016 to December 2016, different search volumes may appear for the same dates, because the highest point in the interval may be different. Besides, even if the same interval is drawn, if it is obtained in a different time, there may be slight changes in values, because google search obtains data as a random subset of historical data.

In addition, data is adjusted for population so that searches from highly populated cities do not crowd out other cities. To do so, data is divided by the total searches of the geography. Thus, in order to show an increase, a topic should increase its proportion within all the searches in its' geography. This way whole country's searches are reflected more accurately. Use of country filter is also essential if the aim is to get the interest of only a certain country. Country filter is another important feature of Google Trends. When worldwide searches are selected this would show searches for that keyword from all around the world. However, words or abbreviations may have common meanings in different languages, and this may lead to overestimation of some searches. Hence, selection of country or region is crucial.

3.3 Use of Google Trends in Academic Studies

Google Trends has been used by many scholars and businesses in various areas. One of the main areas internet search volume is used is economics research. Ettredge et al. (2005) employed internet search data to predict unemployment rate in the United States. Choi and Varian (2009) and Choi and Varian (2011) state that economic data is usually published with a lag. Thus, they state that an alternative and more timely measure is needed. They use Google Trends's internet search data to nowcast the automobile sales, unemployment benefits, travel destination planning, and consumer confidence. They mention nowcasting, rather than forecasting because they aim at determining Google's ability to predict the present, but without a lag, while they do not examine its forecasting power. D'Amuri and Marcucci (2010), also made a study for US unemployment rate and found that Google search data outperforms other methods of unemployment forecasting. Askitas and Zimmermann (2009) also tested Google's relevance for forecasting German unemployment rates and found strong relationship between Google search volume and unemployment. Suhoy (2009) studied the power of Google search in forecasting economic growth of Israel, by determining its relationship with key economic indicators such as Human Resources (Recruitment and Staffing), Home Appliances, Travel, Real Estate, Food and Drink and Beauty and Personal Care. McLaren and Shanbhoge (2011), on the other hand, show Central Banks benefit from Google Trends as a source of data.

Radinsky et al. (2009), Huang and Penna (2009), and Preis et al. (2010) benefit from Google Search volume to measure consumer sentiment.

Schmidt and Vosen (2009) used Google Search data's for predicting private consumption while Lindberg (2011) studied its relationship with retail sales. Wu and Brynjolfsson, on the other hand, tested Google's ability to predict house sales and prices, and found that Google is very functional in forecasting these measures.

Internet search data is also frequently used in health research. Cooper et al. (2005) used Yahoo search volume for their cancer related research. Polgreen et al. (2008) showed that internet search data can be effective in predicting influenza like diseases. Ginsberg et al. (2009) also suggested to use Google Trends to predict influenza outbreaks by showing that people start to search flu related keywords 1-2 weeks Centers for Disease Control and Prevention (CDC) reports.

Google Trends has also been used in many studies in finance. They will be explained in detail in the next section.

4. GOOGLE SEARCH AND STOCK RETURNS: A STUDY ON BIST 100 STOCKS

4.1 Introduction

Relationship between Google search and stock returns is an exciting topic of research. By observing that there is an increase in investor attention for a certain stock, traders can also buy these stocks and make significant profits. This would be a huge opportunity for traders. Therefore, a number of researchers' tried to confirm the existence of such a relationship.

4.2 Literature Review

Efficient market hypothesis (EMH) states that prices reflect all available information (Fama, 1976). However, Kahneman (1973) states that investors have scarce attention. Therefore, it is not possible for investors to have all information about all stocks. EMH implies that it is impossible to beat the market by employing various techniques. Nevertheless, some researchers who studied the relationship between internet search and stock returns and concluded that significant profits can be made when stocks with high search volumes are bought. Merton (1978) also states that investor attention affects stock prices and liquidity.

There are already some conventional proxies for investor attention such as, extreme returns, trading volume, news, advertising expense, and price limits. Barber and Odean (2008) show that individual investors are net buyers of attention grabbing stocks (stocks on the news, stocks with abnormal trading volumes, and stocks whose previous day's return are extreme). They first determine that individual investors are net buyers of stocks in the news. Then they prove that individual investors are net buyers of stocks with high trading volumes, and will be net sellers of stocks whose trading volume are low. Third, they show that individual investors are net buyers of stocks with extremely negative and positive previous day's returns. They use previous day's return because investors are more likely to realize the increase in prices only after market closes. After being aware of the extreme return, they react to that by buying, which increases prices further. The hypothesis they put forth here is that investor attention causes a temporary increase in prices, which is called price pressure.

However, conventional proxies such as news, returns and trading volume are indirect and have shortcomings. Da et al. (2011) first prove that correlation of Google search volume with news, trading volume and return are low. Low correlation they find between Google search volume and news signals that a particular news may not reach enough investors. People do not have enough time to monitor all news whole day. Thus, some news may go unnoticed. Besides, supposing that the news reached the investors, investors may interpret the news differently. That is, some investors can regard the news as a good one that may increase the price and decide to trade, while others may find the news irrelevant to the price of the stock. Second, they state that low correlation of trading volume and return with search volume implies that an increase in return or trading volume can be due liquidity or information related trades, which are separate from investor attention. Then, they eventually find that search volume leads news, trading volume, and return. This means that investors make internet search before they buy stocks, so that internet search leads price and trading volume increases. Given that people search stocks on internet before news such as earnings announcements, it is understandable that SV leads news.

Relationship between Google search and stock returns has been studied by some scholars. Most of the studies found a temporary increase in stock returns, which reverts in coming weeks or within a year. This behavior is the so called “price pressure” in stocks that attract investors’ attention.

Barber and Odean (2008) state that individual investors are net buyers of stocks that attract attention. In detail, they prove that individual investors are net buyers of stocks whose previous day’s returns were exceptionally negative or positive, stocks whose trading volume is high and stocks in the news. They state that investors do not buy all stocks that catch their attention, but the ones that they buy are among attention grabbing stocks. They also indicate that individual investors do not face the same search problem when seeling because of two main reasons. First of all, individual investors hold relatively few stocks in their portfolios. Second, they do not usually sell short. Therefore, they can make their decision about selling or not selling one by one for each stock in their portfolio. Authors also determine that attention affects the buying behavior of individual investors much more than it affects the behavior of institutional investors. Unlike individual investors, institutional investors hold more stocks in their portfolios, and they frequently sell short. Attention is not scarce for them given that it is their job to monitor stocks regularly. Besides they benefit from their sophisticated computer softwares to put specific criteria (e.g. profitability ratios) and narrow their search. Hence they do not neet to narrow their search by attention.

Da et al. (2011) studied the relationship between Google search and stock returns for stocks in Russell 3000 index in the US. They use all 3606 stocks in the index from January 2004 to June 2008. They show that although Google search is correlated with the existing proxies of investor attention such as (extreme returns, trading volume, news and headlines and advertising expense), it is different from them. Existing proxies such as extreme returns, trading volume and news have a number of drawbacks. First of all, it may be factors other than investor attention behind the increase in return or turnover. Moreover, investors do not necessarily read the news. They also find that unlike existing proxies, Google search catches investor attention on time. They also evidence that Google search reflects the attention of individual investors. Their results show that an increase in google search is followed by an increase in the next two weeks and which reverts within a year. They find that price pressure effect is more prevalent for small stocks. Authors also state that investor attention and thus price pressure may be behind the first day overpricing and long run underperformance of IPO stocks, which confirms the notion of marketing role of IPOs shown by Demers and Levellen (2003).

Joseph et al. (2011) study the same relationship for S&P500 stocks from 2005 to 2008. They use the four factor model of Carhart (2007) to determine stock returns, which includes a momentum factor to the existing three factors presented by Fama and French (1993). They show that Google search volume is effective in forecasting abnormal stock returns and trading volume by proving that there is an increase in stock returns one week after an increase in Google search, which again reverses after week five. They also show that the returns are more sensitive for difficult to arbitrage (high volatility) stocks and less sensitive for easy to arbitrage stocks.

Bank et al. (2011) look at the topic also from a different perspective. They state that by searching on Google investors not only gather information about financials, they also gather product information, which may indirectly affect stock choice as stated by

Frieder and Subrahmanyam (2005). For this reason they use company names as search keyword. They find that increase in search volume is followed by an increase in stock liquidity. They attribute this increase in stock liquidity to reduced asymmetric information costs, which signals that search volume captures the attention of individual investors. They also find that there is a temporary increase in stock returns following an increase in Google search volume, which further confirms the existence price pressure. In their analysis, they use all stocks on XETRA from 2004 to 2012, and stock and internet search data used is weekly.

Latoeiro et al. (2013) also tried to study the effect of Google search volume on stock market. They cover the stocks on EURO STOXX index in their study. They prove that in response to an increase in Google search volume there is a temporary increase in volatility and trading volume, and a decrease in cumulative returns. One possible explanation for the decrease in cumulative returns is that once their attention increases, investors realize the stocks that increased, and sell them, which causes the prices to decrease. The increase in volatility and trading volume reverses after one week which they attribute to unprofessional investors. They also find that increase in search volume of index is followed by a decrease in index return and stock index futures, and an increase in implied volatility. It is seen that the results do not imply price pressure hypothesis, which is attributed to the large stocks in the sample. Predictability of Google search volume increases in periods where firm and market prices reach 52-week-high and it decreases in periods where market is at 52-week low. Authors also show that investors are more likely to evaluate market information than firm specific information, which verifies limited attention theory.

Auadi et al. (2013) study the effect internet search interest on stock market activity. They use French stocks listed on CAC 40 and use weekly data between 2004 to 2010. They find that there is a strong link between Google search volume and tradign volume. They also show that internet search interest affects stock market liquidity and volatility.

Takeda and Wakao (2014) studied the relationship of Google search with stock returns and trading volume in Nikkei 225 stocks of Japan. They use weekly data from January 2008, to December 2011. They found that Google search volume is strongly related to trading volume and weakly related to stock returns. The weak correlation between Google search volume and stock return is attributed to two factors. The authors, first of all, state that majority of investors in Japan are institutional investors. Then, they point out that Yahoo is the most popular search engine in Japan and it has a market share of 50-60%, while Google is the second most popular search engine with a market share of 30-40%. Therefore, they concluded that Google search data may not be a representative of Japanese population.

Turan (2014), studied the relationship between internet search volume and stock return volatility in 10 stocks in BIST 100 index. It is shown that Google search interest affects stock return volatiliy. Another implication is that Google search interest and trading volume together also affect stock return volatility. The author also shows that heteroscedasticity in the stock return can not be explained by internet search interest or both internet search interest and trading volume completely.

Korkmaz et al. (2017) study the relationship of Google search volume and BIST 100 Index. They used weekly data between 2004 and 2016 in their analysis. They tried to understand whether investor attention causes an increase in index return and trading volume or index return and trading volume themselves attract investors' attention and makes them search the stocks. To do so, they employed Granger Causality test and Impulse-Response Function. They show that the direction of causality is from index return and trading volume to Google search volume. However, not all the time index return attracts attention. They find that investors are more interested in BIST when index is low, while they are less interested when index is high. They also show that trading volume is an important factor that affects Google search volume.

Use of internet data in financial markets is not limited to Google Trends. Various studies have been made to prove that Twitter data may be relevant for stock market. Bollen et al. (2010), Sprenger and Welpe (2010), and Zhang et al. (2011), Ruiz et al. (2012) employed Twitter mood to predict stock market movements, while Loughlin et al. (2013) made use of StockTwits and Google Trends. Öztürk and Çiftçi (2014), on the other hand, studied the relationship between Twitter messages and USDTRY.

Barber and Odean (2008) state that the main rationale behind buying attention grabbing stocks is scarcity of attention. Choosing from thousands of stocks is not an easy task and investors solve this problem by focusing only on attention grabbing stocks (stocks in the news, stocks with high abnormal trading volume, and those whose previous day returns are abnormal). To be more clear the they state that investors do not buy all stocks that catch their attention, but the stocks that buy are most of the time among attention grabbing ones. This means that they limit the stocks to attention grabbing ones then choose according to their preferences.

While they differ from each other by terms of proxies they use Barber and Odean (2008) and Da et al. (2011) both assert that investor attention affects individual (retail) investors more than institutional investors. First of all, individual investors usually do not sell short. And since they hold only a few stocks in their portfolios, they can consider selling or holding stocks one by one. Institutional investors, however, sell short continually. What's more, their attention is not scarce, given that it is their job to make research about stocks. Therefore, they do not need attention grabbing stocks to narrow their search. Besides they have access to sophisticated trading platforms such as Bloomberg or Thomson Reuters so that they can benefit from financial ratios and many other factors to narrow down stocks. These facts explain why searches that are made signal buying than selling.

Type of stocks that are more sensitive to search volume has also been researched by many researchers. Some scholars who studied the relationship between Google search and stock returns found that price pressure is more likely to be observed in small stocks, while others showed that large cap stocks are more sensitive to internet search interest. Da et al. (2011) and Takeda and Wakao (2014) showed that the price pressure effect is stronger in small stocks. Bank et al. (2011), on the other hand proved that portfolios that include highly searched and high market cap stocks outperform those which include least searched and low market cap stocks. Joseph et al. (2011), on the other hand, state that the effect is stronger for hard to arbitrage stocks, that is, for the stocks that are more volatile. This is in line with Baker and Wurgler (2007)'s findings, who find that low market capitalization stocks are hard to arbitrage and more difficult to value. Baker and Wurgler (2007) state that valuation of a new and small firm ican be very difficult because there is not enough earnings history and future income can not be predicted clearly. This leads to different valuations by different investors. Some investors overvalue these stocks while others undervalue them, according to their sentiment.

4.3 Data and Market

Google Search Volume is a direct measure of investor attention and is being used in recent studies. Da et al. (2011) state that investors search for a particular stock only if they are paying attention to it. Therefore, google search is a novel and direct measure. Besides, google is the most commonly used search engine globally and in Turkey. As of December 2017 Google had a 87.1% of searches were made in Google globally (URL2). As of March 2018 it has a 96.74% market share in Turkey (URL3). This shows that Google is a good representative of the turkish population.

Most important characteristic of Google search volume data is that it is not absolute but relative. When search volume of a keyword for a specific time interval (i.e. from May 2016 to September 2017) is to be obtained, the day with the most searches within the interval is scored as 100 and the remaining days are graded relatively. For example, the day with half as much searches as the day with highest searches is given 50. Moreover, days, whose search volume is less than 1% of the day with the highest searches, are scored as 0. Therefore, if a greater data is drawn which includes the same interval but is greater than it such as January 2016 to December 2016, different search volumes may appear for the same dates, because the highest point in the interval may be different. Another important feature is that Google search volume data generated as a random subset of historical data so that some days can have a different score when two data are drawn from two different points in time. The scores that represent Google search volume will be referred to as SV in the analysis.

Choice of Google search keyword is critical to the robustness of the research. Bank et al. (2011) use company name in their study, because they think that product related search is also relevant for the returns. However, if a general keyword such as company name is used, it can be misleading. This search may be for company’s products rather than stock information, or they can be for a sports team that the company is sponsoring. Not to mention other purposes such as human resources websites, store locations. Takeda and Wakao (2014), who also used company name as keyword, try to overcome this by eliminating irrelevant purposes. This is possible by subtracting the unrelated topic with a minus after the company name, which is a feature of Google that is not frequently used on a daily basis. However, this is a very challenging and imperfect approach. First of all, listing all the irrelevant keywords and eliminating them properly is quite difficult. Even if all unrelated keywords are eliminated, the remaining search volume becomes very low that Google Trends can not show anything. An alternative would be a combination of two words (for example: Dogus stock), so that it reflects investment purpose. Although this sounds logical, search volumes for such a combination are low for majority of stocks so that most days appear as zero. Hence, this method is not selected. To overcome these difficulties, Da et al. (2011) and Joseph et al. (2011) used stock ticker symbols as keywords in their studies. It is logical to use stock ticker because tickers are distinctly different from company names. Thus when someone uses the ticker, it is clear that she is interested in stock information rather than other purposes.

Only the searches made from Turkey are used because of two reasons. The main reason is of course to capture Turkish investors behavior. Moreover, words or abbreviations may have common meanings in different languages, and this may lead to overestimation of some searhes if searches are not limited to a certain country. Thus, the searches are limited to Turkey in the study.

The stocks used in the study are those in BIST100 Index as of August 2017. The index constitutients are obtained from Borsa Istanbul official website. BIST100 is the most comprehensive index covering the largest companies by market capitalization. The data used is weekly data from September 2012 to August 2017. Return data, market capitalization data and price to book ratios, risk free rate and market return data are used in the analyses. They were all obtained from Thomson Reuters. For 258 sample weeks (approximately 5 years), and 100 stocks, there were 25800 observations in the analysis.

4.4 Methodology

Two types of analyses are made in this study. First, separate OLS regressions are run on 100 sample stocks. It is then determined whether Google search volume is an explanatory variable. Second, following the literature (Joseph et al., (2011); Bank et al., (2011); and Takeda and Wakao, (2014)) stocks are grouped into four different portfolios based on their Google search volume, and regressions are run on these four portfolios. This way it will be seen whether going long on highly searched stocks generates more returns.

4.4.1 Individual regressions

Following Bank et al. (2011) and Takeda and Wakao (2014) Fama-French three factor model is used in this analysis. In **(4.1)** is the equation of the OLS regressions run for 100 stocks.

$$R_{i,t} - R_{f,t} = \alpha + \beta_1 SV_{t-1} + \beta_2 (R_{m,t} - R_f) + \beta_3 SMB_t + \beta_4 HML_t + \epsilon_{Qk,t} \quad (4.1)$$

Where small minus big (SMB) is the return difference between stocks with low and high market capitalization, that is small and big stocks, while high minus low (HML) is the return difference between stocks with high and low book to market equity, that is value and growth stocks. R_m-R_f is the market risk premium, and beta is stock's volatility. α symbolizes abnormal return. SV represents the Google search volume. Significant β_1 would mean that Google search volume is an explanatory variable in determining stock prices. β_1 is expected to be meaningful either positive or negative. A positive beta would mean that there search volume has an effect on excess returns and contains information about future stock prices, while a negative beta would mean that when investors search for stocks abnormal returns decrease, this may in fact imply selling rather than buying after, which would challenge the prevalent opinion that investors search for buying rather than selling.

Nevertheless, it is not that straightforward and Google search volume should be used carefully. Due to its algorithm, using the search volume provided by Google Trends directly can be problematic. Therefore, three different models are suggested by scholars. In equation **(4.2)** is the Model 1 suggested by Takeda and Wakao (2014), which takes Google search volume as it is. However, Takeda and Wakao (2014) state that since Google search data is relative, because of shocks some days may appear as very low, which may adversely affect the results. They state that an alternative method is needed in addition to Model 1. They suggest taking the difference to eliminate this problem, which is the Model 2 in **(4.3)**, so that returns and all three factors will be regressed not on SV_{t-1}, but $SV_{t-1} - SV_{t-2}$. This way the pattern is seen rather than the absolute number. Nevertheless, Model 2 also has some disadvantages. Search data drawn from Google trends is a random subset of historical data, so that data drawn for the same time interval in two different points of time can be different. That is, the data for 4th of December may be 57 while downloaded in another time it can be 60. In order to tackle this problem, Da et al. (2011) and Takeda and Wakao (2014) used an alternative method, which is based on subtracting the median of search volume in the last seven weeks from current week as in equation **(4.4)**. While each model has its advantages, none of them are worthless and make up a comprehensive approach when used together. As Takeda and Wakao (2014) both three models are used in the analysis.

$$Model\ 1\ at\ time\ t-1: SV_{t-1} \tag{4.2}$$

$$Model\ 2\ at\ time\ t-1: \Delta SV_{t-1} \tag{4.3}$$

$$Model\ 3\ at\ time\ t-1: SV_{t-1} - Median(SV_{t-2}, SV_{t-3}, \dots, SV_{t-8}) \tag{4.4}$$

Most of the existing studies, especially the ones that found weak relationship, regressed stock returns failed to determine the direction of the relationship, that is whether increase in Google search is followed by an increase in stock return or stock returns themselves may attract attention. In order to figure out this detail, returns are also regressed on search volume (SV) at time t and t+1. So that there will be three models such as Model 1, Model 2 and Model 3 and three time points such as t-1, t and t+1 so that there are nine combinations. This is a unique approach given that the direction of the relationship is overlooked by most of the existing studies. Only Korkmaz et al. (2017) tried to determine the direction of the returns, though this study was applied on the index, not on the stocks themselves.

4.4.2 Group regressions

In the second part of the analysis, following Joseph et al. (2011), Bank et al. (2011), Latoeiro et al. (2013) and Takeda and Wakao (2014), stocks are grouped into 4 different quartiles based on their search volumes. Q1 represents the stocks whose search volume are the lowest, and Q4 represents the stocks whose search volume are the highest at time. Portfolios are rebalanced in the beginning of each week, so that Q1 is always the portfolio of least searched stocks and Q4 is always the portfolio of most searched stocks. Returns of these four portfolios are then regressed on search volume, market risk premium, SMB, HML as in equation **(4.5)**. If there really is a relationship between internet search stock returns, Q4 should generate the most abnormal returns so that (α) becomes meaningful. Q1, on the other hand, should generate the least abnormal returns.

$$R_{Qk,t} - R_{f,t} = \alpha + \beta_1\left(R_{m,t} - R_f\right) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{Qk,t} \qquad (4.5)$$

Returns of the portfolios are simply calculated as the average of stocks as in **(4.6).**

$$R_{Qk,t} = \frac{\Sigma \mathrm{A_{it}}}{n} \qquad (4.6)$$

Where A_{it} is a stock's individual return at time t. Each portfolio's return is simply calculated as the average of stocks in that portfolio. These portfolio returns are represented as $R_{Qk,t}$.

As in the first analysis, stocks are sorted by using three different models. Model 1 in eq. **(4.2)** takes the search volume as it is. Model 2 in eq. **(4.3)** takes the difference of the search volume from last week to current week. and Model 3 in eq. **(4.4)** is based on subtracting the median of search volume in last seven weeks from current week. Also, as in the first analysis, search volume of three different times is used. Search volume of t-1, t and t + 1 is used to sort the stocks, separately. This way it will be seen whether Google search precedes increase in stock returns or investor attention increases as a result of abnormal returns. Thus, there will be nine combinations of search interest.

4.5 Emprical Findings

In this part, first the results of individual regressions will be presented. Then results of the four portfolios will be given.

4.5.1 Individual regressions

Regression results for each BIST 100 stock are given in the Appendix A. Summary of these results of are given in Table (4.1), Table (4.2), Table (4.3).

Table 4.1: Number of stocks in which β of search volume (SV) was significant in individual regressions

	t-1			t			t+1		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
α=0.01	2	2	2	26	35	37	23	8	32
α=0.05	11	4	8	38	45	47	39	17	42
α=0.10	17	8	9	46	58	52	42	26	48

Note: Number of BIST 100 stocks in which beta (β) of SV was significant in individual regressions (equation **(4.1)**). First column represents level of significance. First row represents time in which Google search volumes are obtained. At time t-1, search volumes for t-1 is regressed on returns of t. At time t, search volumes for t is regressed on returns of t. At t+1, search volumes for t+1 is regressed on returns of t. Second row represents search volumes according to three different models. Model 1 is the search volume in its original form provided by Google Trends (SV_{t-1} or SV_t, or SV_{t+1} according to the time). Model 2 is difference in search volume from last week to current week ($SV_{t-1} - SV_{t-2}$ or $SV_t - SV_{t-1}$ or $SV_{t+1} - SV_t$ according to the time). Model 3 is the increase in search volume from median of the last 7 weeks to the current week (SV_{t-1} – Median($SV_{t-2}, SV_{t-3},\ldots,SV_{t-8}$) or SV_t – Median($SV_{t-1}, SV_{t-2},\ldots,SV_{t-7}$) or SV_{t+1} – Median($SV_t, SV_{t-1},\ldots,SV_{t-6}$)).

Table 4.2: Number of stocks in which β of search volume (SV) was significantly positive in individual regressions

	t-1			t			t+1		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
α=0.01	2	0	2	26	35	36	22	4	30
α=0.05	5	0	4	35	44	46	35	6	39
α=0.10	7	1	4	43	56	50	37	11	42

Note: Number of BIST 100 stocks in which beta (β) of SV was significantly positive in individual regressions (equation **(4.1)**). First column represents level of significance. First row represents time in which Google search volumes are obtained. At time t-1, search volumes for t-1 is regressed on returns of t. At time t, search volumes for t is regressed on returns of t. At t+1, search volumes for t+1 is regressed on returns of t. Second row represents search volumes according to three different models. Model 1 is the search volume in its original form provided by Google Trends (SV_{t-1} or SV_t, or SV_{t+1} according to the time). Model 2 is difference in search volume from last week to current week ($SV_{t-1} - SV_{t-2}$ or $SV_t - SV_{t-1}$ or $SV_{t+1} - SV_t$ according to the time). Model 3 is the increase in search volume from median of the last 7 weeks to the current week (SV_{t-1} – Median($SV_{t-2}, SV_{t-3},\ldots,SV_{t-8}$) or SV_t – Median($SV_{t-1}, SV_{t-2},\ldots,SV_{t-7}$) or SV_{t+1} – Median($SV_t, SV_{t-1},\ldots,SV_{t-6}$)).

Table 4.3: Number of stocks in which β of search volume (SV) was significantly negative in individual regressions

	t-1			t			t+1		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
α**=0.01**	0	2	0	0	0	1	1	4	2
α**=0.05**	6	4	4	3	1	1	4	11	3
α**=0.10**	10	7	5	3	2	2	5	15	6

Note: Number of BIST 100 stocks in which beta (β) of SV was significantly negative in individual regressions (equation **(4.1)**). First column represents level of significance. First row represents time in which Google search volumes are obtained. At time t-1, search volumes for t-1 is regressed on returns of t. At time t, search volumes for t is regressed on returns of t. At t+1, search volumes for t+1 is regressed on returns of t. Second row represents search volumes according to three different models. Model 1 is the search volume in its original form provided by Google Trends (SV_{t-1} or SV_t, or SV_{t+1} according to the time). Model 2 is difference in search volume from last week to current week ($SV_{t-1} - SV_{t-2}$ or $SV_t - SV_{t-1}$ or $SV_{t+1} - SV_t$ according to the time). Model 3 is the increase in search volume from median of the last 7 weeks to the current week (SV_{t-1} – Median(SV_{t-2}, SV_{t-3},…,SV_{t-8}) or SV_t – Median(SV_{t-1}, SV_{t-2},…,SV_{t-7}) or SV_{t+1} – Median(SV_t, SV_{t-1},…,SV_{t-6})).

When the results for time t-1 is observed, for Model 1, for 0.05 level of significance, in 5 out of 100 stocks there was a positive and significant relationship, and this increases to 7 for 0.1 level of significance. However, for 0.10 level of significance in 10 out of 100 stocks there was a negative and signficant relationship. For Model 2, in almost none of the stocks there was a positive and significant relationship, for any level of significance. Nevertheless, in 4 out of 100 stocks there was a negative and significant relationship, for 0.05 level of significance. For Model 3, for 0.05 level of significance, in 4 out of 100 stocks there was a positive and significant relationship, while in 4 out of 100 stocks there is negative and significant relationship also for 0.05 level of signifance. The overall results for time t-1 reveal that there is almost no relationship between searches made in t-1 and stock returns in t.

The results for time t are actually remarkable. For Model 1, for 0.05 level of significance. In 35 out of 100 stocks there was a positive and significant relationship, while in very few stocks there was a negative and significant relationship. For Model 2, for 0.05 level of significance, in 44 out of 100 stocks there was a positive and significant relationship, while in almost none of the stocks there was a negative and significant relationship. For Model 3, the results are even stronger so that in 46 out of 100 stocks there was positive and significant relationship for 0.05 level of significance.

These results show that the returns at time t are positively related to searches made at time t.

For time t+1 there are also some notable results. For Model 1, for 0.05 level of significance, in 35 out of 100 stocks there was a positive and significant relationship, while in only 4 stocks there was a negative and significant relationship, for the same level of significance. For Model 2, for 0.05 level of significance, in 6 out of 100 stocks there was a significant relationship, however, for the same level of significance in 11 out of 100 stocks there was a negative and significant relationship. This shows that negative results are dominant for Model 2 in t+1. For Model 3, on the other hand, in 39 out of 100 stocks there was a positive and significant relationship for 0.05 level of significance, while in very few stocks there was a negative relationship.

4.5.2 Group regressions

The results of group regressions are given in Table (4.4). Overall, they are in line with the results of individual regressions, but also reveal some more detailed information.

Table 4.4: Results of abnormal returns (α) group regressions

		t-1			**t**			**t+1**		
		Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Q1	Coeff	0.52	0.29	0.25	0.16	-0.08	-0.02	0.18	0.45	0.07
	P-value	0.0042	0.1205	0.1935	0.3189	0.6582	0.9069	0.2974	0.0233	0.7027
Q2	Coeff	0.46	0.47	0.42	0.26	0.15	0.08	0.34	0.35	0.12
	P-value	0.0184	0.0114	0.0285	0.1739	0.3832	0.6512	0.0791	0.0589	0.4975
Q3	Coeff	0.30	0.50	0.58	0.47	0.42	0.39	0.36	0.24	0.37
	P-value	0.1130	0.0108	0.0023	0.0152	0.0253	0.0376	0.0622	0.1768	0.0434
Q4	Coeff	0.29	0.31	0.39	0.68	1.08	1.16	0.69	0.51	1.04
	P-value	0.1177	0.0919	0.0471	0.0008	0.0000	0.0000	0.0007	0.0097	0.0000

Note: Abnormal returns (α) of OLS regressions for four portfolios Q1, Q2, Q3 and Q4 in Fama French three factor model as in equation **(4.5)**. Portfolios are generated according to their search volumes at time t-1, t and t+1. Q1 consists of least searched stocks, while Q4 consists of the most searched stocks. Model 1 is the search volume in its original form provided by Google Trends (SV_{t-1} or SV_t, or SV_{t+1} according to the time). Model 2 is difference in search volume from last week to current week ($SV_{t-1} - SV_{t-2}$ or $SV_t - SV_{t-1}$ or $SV_{t+1} - SV_t$ according to the time). Model 3 is the increase in search volume from median of the last 7 weeks to the current week (SV_{t-1} – Median($SV_{t-2}, SV_{t-3},\ldots,SV_{t-8}$) or SV_t – Median($SV_{t-1}, SV_{t-2},\ldots,SV_{t-7}$) or SV_{t+1} – Median($SV_t, SV_{t-1},\ldots,SV_{t-6}$)).

The results for Model 1 at time t-1 show that there is no upward pattern in abnormal returns from Q1 to Q4. In fact, there is a reverse pattern so that least searched stocks provided the most returns. P-value of abnormal returns of Q1 and Q2 is 0.0042 and 0.0184, respectively, which signal that least stocks offered significant abnormal returns. Most searched stocks, on the other hand, experienced the least returns and their abnormal returns are not significant. For Model 2 there is no clear pattern from Q1 to Q4. Interestingly, in this Model, returns of Q2 and Q3 are significant, whose P-values are 0.0114 and 0.0108 respectively. For Model 3, there is an increase in abnormal returns from Q1 to Q3 and abnormal returns of Q2 and Q3 are both significant. However, this pattern reverts after Q3, but Q4's abnormal return is still significant for 0.05 level of confidence.

Results of time t is in compliance with individual regressions. For Model 1, there is an increase pattern in coefficients from Q1 to Q4 so that p-value of Q3 and Q4 are both significant. Significance of abnormal returns in Q3 and Q4 means that most searched stocks experienced the most returns. For Model 2, also there is an increase in coefficients of abnormal returns from Q1 to Q4. And Q3 and Q4 are both significant (0.0253 and 0.0000 respectively). For Model 3 also there is a clear increase in coefficients of abnormal returns from Q1 to Q4. P-values of abnormal returns of Q3 and Q4 are both significant (0.0376 and 0.0000 respectively).

For time t+1 results are similar to time t to some extent. For Model 1, there is an increase in coefficients of abnormal returns from Q1 to Q4 and p-value of Q4 is significant 0.0007. For Model 2, however, there is not a clear pattern in abnormal returns. Yet, returns of Q1 and Q4 are significant. Results of Model 3 are similar to Model 1, which implies that abnormal returns gradually increase from Q1 to Q4 and p-values of Q4 are both significant.

4.6 Discussion of the Results

The results show that there is a positive and significant relationship between searches made at time t and abnormal stock returns at time t. There is also a positive and significant relationship between searches made at time t+1 and stock returns at time t. However, no relationship is observed between searches made in t-1 and abnormal returns at time t, which makes it hard to make an implication.

If the results for time t-1 were significant, then this would clearly mean that the direction of the relationship is from Google search to stock returns, so that after searching on Google people buy certain stocks which increases the returns. Results for time t, however, are hard to interpret. There is significant correlation between search interest at time t and abnormal returns at time t, but since the data is weekly, it can not be clearly seen on which day of the week search interest starts to increase and on which day returns start to increase. If the search interest increases in Monday and stock returns increase in Wednesday, this would mean that search interest precedes stocks returns. However, if the returns increase in Tuesday and search interest increases in Friday, this would imply that people are searching for well performing stocks. Therefore, it is not clear whether the Google search precedes increase in returns, or returns themselves attract attention.

However, there is also strong relationship between returns at time t and searches made at time t+1. This implies that the direction of the relationship may be from abnormal returns to Google search, that is, abnormal return in a certain stock attracts investors' attention and make them search the stocks in internet. In fact, weekly and daily top performers are usually referred to in newspapers and investing and clearly they attact attention.

In this case, it is not possible to generate profits by going long on most searched stocks or going short on least searched ones. This actually shows efficiency of the Turkish market.

These results confirm the work of Takeda and Wakao (2014), who found that search interest has a weak affect on stock returns for their study in Japanese market. They are also in accordance with the results of Korkmaz et al. (2017) who found that the direction of returns is from extreme returns to internet search on their analysis on BIST 100 index. However, studies of Da et al (2011), Joseph et al. (2011) and Bank et al. (2011) are challenged with these results, who found that there is an increase in the following weeks after an increase in internet search volume that disappears with time.

5. CONCLUDING REMARKS

Increase in internet usage around the world offers researchers many opportunities. It gives insights into almost everything about users, from what they eat to where they travel, even the questions that instantly appear in their minds, which makes it very valuable to the scholars. Google is certainly one of the most valuable sources of data. Fortunately, Google Trends shares the volume of queries made in Google search engine. Data offered by Google is very critical to finance research and it has been used frequently in the recent years. Investor attention is one of those areas. Some scholars tried to capture investor attention through Google search volume and try to predict stock returns.

In this study, existence of the relationship between Google search volume and stock returns in BIST100 stocks is examined. To do so, two separate analyses are conducted. First, the stock returns are regressed on Google search volumes in Fama French three factor model for 100 stocks, in order to find out whether there is a positive and significant relationship between Google search volume and stock returns. In the second part of the analysis, stocks are sorted into four different portfolios based on their search volumes. OLS regressions are made for returns of these four portfolios in Fama French Three Factor Model in order to find out whether portfolio of most searched stocks generates more abnormal returns than the portfolio of least searched stocks.

The results show that there is a linkage between Google search volume and stock returns. Yet, direction of the relationship is different from some studies made for other markets. It is observed that increase in returns precedes increase in Google search volume for stocks. This means people search for stocks that generated most returns. Thinking that top performers are quoted in many newspapers, finance websites, it makes sense that this attracts attention. This is actually in accordance with the Efficient Market Hypothesis, which foresees that it is not possible to beat the market. Therefore, this result shows efficiency of the Turkish market.

Results of this study can be rendered with an analysis with the daily data. There is also a positive and significant relationship between Google search and stock returns at time t. Nevertheless, it is not easy to conclude that Google search precedes stock returns, because it is not clear in which day of the week the search interest starts to increase and in which day the returns increase. Hence, direction of the relationship at time t can not be determined with weekly data. With daily data it can be understood on which day the search interest and returns increase and direction of the relationship could be revealed.

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APPENDIX

APPENDIX A: Results of Individual Regressions

APPENDIX A

RESULTS OF INDIVIDUAL REGRESSIONS

TABLE A.1: Coefficients and P-values of β of search volume (SV) in individual regressions

		t - 1			t			t + 1		
		Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
AEFES	**Coeff**	0.0003	-0.0230	-0.0189	-0.0085	-0.0069	-0.0244	0.0007	0.0073	-0.0077
	P-value	0.9852	0.0662	0.2117	0.5482	0.5838	0.1060	0.9614	0.5640	0.6085
AFYON	**Coeff**	-0.0388	-0.1524	-0.1517	0.0217	0.3243	0.1527	0.0427	0.1210	0.2149
	P-value	0.5907	0.2942	0.3400	0.7610	0.0504	0.3353	0.5519	0.4650	0.1743
AKBNK	**Coeff**	-0.0036	0.0047	-0.0058	0.0096	0.0092	0.0080	-0.0468	-0.0406	-0.0427
	P-value	0.8576	0.7732	0.7704	0.6331	0.5835	0.6902	0.0177	0.0147	0.0298
AKENR	**Coeff**	-0.0042	-0.0103	0.0071	0.0611	0.0966	0.1108	0.0356	-0.0408	0.0602
	P-value	0.7902	0.5960	0.7306	0.0001	0.0000	0.0000	0.0252	0.0345	0.0034
AKSA	**Coeff**	-0.0328	-0.0026	-0.0316	-0.0131	0.0158	-0.0099	0.0082	0.0172	0.0146
	P-value	0.2703	0.9235	0.3127	0.6591	0.5543	0.7505	0.7848	0.5208	0.6412
AKSEN	**Coeff**	-0.0009	-0.0198	-0.0049	0.0143	0.0137	0.0156	0.0144	0.0002	0.0094
	P-value	0.9668	0.3584	0.8464	0.5265	0.5228	0.5377	0.5246	0.9912	0.7101
ALARK	**Coeff**	0.0066	-0.0085	-0.0134	0.0418	0.0338	0.0370	0.0336	-0.0061	0.0202
	P-value	0.6765	0.5813	0.4762	0.0072	0.0266	0.0456	0.0318	0.6923	0.2783
ALCTL	**Coeff**	-0.0202	-0.0592	-0.0409	0.0510	0.1205	0.0694	0.1104	0.1044	0.1495
	P-value	0.4743	0.1119	0.2569	0.0710	0.0009	0.0573	0.0001	0.0046	0.0000
ALGYO	**Coeff**	-0.0231	0.0267	-0.0209	0.0465	0.1076	0.0842	0.0622	0.0237	0.1156
	P-value	0.2070	0.2441	0.3664	0.0109	0.0000	0.0002	0.0007	0.3029	0.0000
ALKIM	**Coeff**	0.0089	0.0370	0.0166	0.0780	0.0352	0.0854	0.0792	0.0023	0.0811
	P-value	0.8680	0.3439	0.7573	0.1485	0.3621	0.1122	0.1361	0.9535	0.1269
ANACM	**Coeff**	0.0056	0.0100	-0.0092	0.0275	0.0235	0.0417	0.0226	-0.0068	0.0327
	P-value	0.7263	0.5324	0.6588	0.0794	0.1471	0.0451	0.1516	0.6786	0.1159
ARCLK	**Coeff**	-0.0043	-0.0132	-0.0154	-0.0103	-0.0047	-0.0256	0.0072	0.0138	0.0007
	P-value	0.7921	0.3637	0.3846	0.5319	0.7467	0.1457	0.6616	0.3480	0.9692
ASELS	**Coeff**	0.0282	0.0449	0.0522	0.0377	0.0669	0.1089	0.0397	0.0114	0.0934
	P-value	0.0600	0.2249	0.1291	0.0100	0.0679	0.0014	0.0066	0.7558	0.0065
AYGAZ	**Coeff**	0.0106	0.0450	0.0232	0.0308	0.0178	0.0447	-0.0203	-0.0424	-0.0244
	P-value	0.7009	0.0809	0.4589	0.2623	0.4898	0.1526	0.4604	0.0995	0.4355

TABLE A.1 (CONTINUED): Coefficients and P-values of β of search volume (SV) in individual regressions

BAGFS	**Coeff**	-0.0103	0.0119	0.0002	0.0172	0.0377	0.0470	0.0096	-0.0105	0.0259
	P-value	0.5267	0.5342	0.9910	0.2907	0.0469	0.0248	0.5580	0.5845	0.2199
BANVT	**Coeff**	0.2428	0.0463	0.1965	0.4044	0.3504	0.3825	0.2497	0.0614	0.1907
	P-value	0.0000	0.4994	0.0039	0.0000	0.0000	0.0000	0.0000	0.2206	0.0000
BIMAS	**Coeff**	0.0026	-0.0092	0.0024	-0.0230	-0.0194	-0.0256	-0.0202	0.0028	-0.0219
	P-value	0.8794	0.5332	0.8933	0.1673	0.1820	0.1367	0.2266	0.8469	0.2080
BIZIM	**Coeff**	0.0015	-0.0565	-0.0188	-0.0016	-0.0181	-0.0419	0.0119	0.0830	0.0083
	P-value	0.9501	0.3229	0.6717	0.9451	0.7510	0.3477	0.6163	0.1495	0.8519
BJKAS	**Coeff**	-0.0428	0.0240	0.0021	0.0076	0.1357	0.1190	0.0984	0.2496	0.3366
	P-value	0.1940	0.6587	0.9679	0.8161	0.0117	0.0185	0.0025	0.0000	0.0000
BRISA	**Coeff**	-0.0288	-0.0221	-0.0313	0.0382	0.0664	0.0396	0.0118	-0.0247	0.0090
	P-value	0.0940	0.2092	0.0777	0.0268	0.0001	0.0241	0.4941	0.1470	0.6101
CCOLA	**Coeff**	-0.0183	-0.0012	-0.0218	-0.0013	0.0150	0.0007	-0.0516	-0.0447	-0.0535
	P-value	0.2694	0.9411	0.1896	0.9351	0.3365	0.9653	0.0019	0.0044	0.0013
CEMTS	**Coeff**	-0.0173	-0.0211	-0.0289	0.0559	0.0759	0.0949	0.0249	-0.0361	0.0490
	P-value	0.4178	0.3344	0.2911	0.0076	0.0004	0.0004	0.2421	0.0971	0.0728
CLEBI	**Coeff**	-0.0031	0.0121	-0.0130	0.0495	0.0386	0.0525	0.0483	-0.0016	0.0509
	P-value	0.9030	0.5766	0.6418	0.0500	0.0746	0.0572	0.0573	0.9406	0.0643
CRFSA	**Coeff**	-0.0247	0.0403	0.0084	0.0232	0.0969	0.1136	0.0205	-0.0520	0.0849
	P-value	0.4029	0.3447	0.8482	0.4197	0.0188	0.0073	0.4650	0.2010	0.0403
DEVA	**Coeff**	0.0183	0.0384	0.0379	0.0349	0.0227	0.0533	0.0523	0.0385	0.0960
	P-value	0.5633	0.2884	0.3487	0.2632	0.5288	0.1854	0.0904	0.2805	0.0154
DOAS	**Coeff**	0.0134	-0.0025	0.0454	-0.0133	-0.0403	-0.0169	-0.0081	0.0076	-0.0059
	P-value	0.5979	0.9373	0.1723	0.6033	0.1984	0.6141	0.7524	0.8091	0.8595
DOHOL	**Coeff**	0.0155	0.0396	0.0936	0.0410	0.1092	0.1552	0.0421	0.0025	0.1431
	P-value	0.3180	0.2038	0.0006	0.0073	0.0005	0.0000	0.0059	0.9381	0.0000
ECILC	**Coeff**	0.0081	0.0109	-0.0092	0.0768	0.1549	0.1750	0.0500	-0.0599	0.0761
	P-value	0.6850	0.7164	0.7705	0.0001	0.0000	0.0000	0.0112	0.0423	0.0155
EGEEN	**Coeff**	-0.0235	-0.0158	-0.0040	0.0163	0.0630	0.0785	0.0363	0.0299	0.0965
	P-value	0.1749	0.4701	0.8722	0.3469	0.0036	0.0014	0.0384	0.1673	0.0001
EKGYO	**Coeff**	-0.0041	0.0132	0.0055	0.0059	0.0131	0.0247	-0.0482	-0.0724	-0.0262
	P-value	0.8517	0.6017	0.8162	0.7856	0.6005	0.2949	0.0270	0.0037	0.2657
ENKAI	**Coeff**	0.0017	0.0093	0.0036	-0.0122	-0.0096	-0.0131	-0.0132	-0.0007	-0.0154
	P-value	0.8874	0.3626	0.7796	0.3214	0.3480	0.3060	0.2853	0.9475	0.2251
ERBOS	**Coeff**	-0.0260	-0.0235	-0.0435	0.1092	0.1781	0.1902	0.0542	-0.0747	0.0831
	P-value	0.2566	0.3699	0.1462	0.0000	0.0000	0.0000	0.0174	0.0041	0.0052
EREGL	**Coeff**	0.0234	0.0196	0.0163	0.0080	-0.0136	-0.0130	0.0156	0.0070	0.0016
	P-value	0.1844	0.2401	0.4060	0.6503	0.4127	0.5058	0.3821	0.6742	0.9335

TABLE A.1 (CONTINUED): Coefficients and P-values of β of search volume (SV) in individual regressions

FENER	**Coeff**	-0.0344	0.0053	-0.0159	-0.0412	-0.0064	-0.0171	-0.0057	0.0309	0.0185
	P-value	0.0416	0.7366	0.3347	0.0135	0.6810	0.2917	0.7354	0.0471	0.2558
FROTO	**Coeff**	-0.0047	0.0122	-0.0104	-0.0437	-0.0359	-0.0549	-0.0121	0.0297	-0.0155
	P-value	0.8022	0.4939	0.6017	0.0185	0.0441	0.0056	0.5203	0.0990	0.4367
GARAN	**Coeff**	-0.0216	-0.0196	-0.0390	-0.0048	0.0229	0.0184	-0.0295	-0.0358	-0.0433
	P-value	0.2341	0.3533	0.1902	0.7920	0.2795	0.5393	0.1056	0.0948	0.1452
GLYHO	**Coeff**	-0.0548	-0.0425	-0.0563	0.0709	0.1370	0.0983	0.0823	0.0101	0.0994
	P-value	0.0934	0.1868	0.1312	0.0163	0.0000	0.0030	0.0053	0.7543	0.0027
GOLTS	**Coeff**	-0.0364	0.0014	-0.0213	0.0423	0.0929	0.0785	0.0727	0.0363	0.1240
	P-value	0.1200	0.9562	0.4243	0.0697	0.0002	0.0027	0.0018	0.1546	0.0000
GOODY	**Coeff**	-0.0936	-0.0286	-0.0571	0.1914	0.3625	0.3203	0.1044	-0.1076	0.1920
	P-value	0.0289	0.5554	0.2516	0.0000	0.0000	0.0000	0.0140	0.0254	0.0001
GOZDE	**Coeff**	-0.0025	-0.0692	-0.0089	-0.0089	-0.0050	-0.0060	0.0524	0.0477	0.0747
	P-value	0.9482	0.0372	0.8304	0.8140	0.8814	0.8846	0.1704	0.1525	0.0721
GSDHO	**Coeff**	-0.0274	-0.0295	0.0071	0.0820	0.0984	0.1002	0.1137	0.0294	0.1253
	P-value	0.2975	0.2322	0.7889	0.0016	0.0001	0.0001	0.0000	0.2284	0.0000
GSRAY	**Coeff**	-0.0569	-0.0291	-0.0764	0.0613	0.2356	0.1079	0.1121	0.0992	0.1878
	P-value	0.0298	0.4284	0.0156	0.0198	0.0000	0.0005	0.0000	0.0074	0.0000
GUBRF	**Coeff**	-0.0499	-0.0352	-0.0473	0.0050	0.0940	0.0750	0.0090	0.0069	0.0675
	P-value	0.0179	0.2037	0.1042	0.8125	0.0006	0.0090	0.6706	0.8051	0.0196
HALKB	**Coeff**	-0.0062	-0.0251	-0.0064	-0.0356	-0.0199	-0.0458	-0.0512	-0.0108	-0.0682
	P-value	0.7851	0.1853	0.7847	0.1185	0.2906	0.0507	0.0246	0.5663	0.0031
HLGYO	**Coeff**	-0.0114	-0.0166	-0.0063	0.0433	0.0491	0.0445	0.0222	-0.0173	0.0239
	P-value	0.3153	0.1218	0.5763	0.0001	0.0000	0.0001	0.0490	0.1052	0.0369
IHLAS	**Coeff**	0.0065	0.0052	-0.0206	0.1275	0.0858	0.1179	0.0498	-0.0561	0.0105
	P-value	0.8834	0.8882	0.6679	0.0038	0.0211	0.0142	0.2649	0.1346	0.8266
IPEKE	**Coeff**	0.0801	0.0020	0.1052	0.1564	0.1798	0.1844	0.1457	0.0068	0.1467
	P-value	0.0340	0.9699	0.0123	0.0000	0.0007	0.0000	0.0000	0.8956	0.0004
ISCTR	**Coeff**	0.0141	-0.0129	0.0001	0.0149	0.0013	0.0006	-0.0042	-0.0267	-0.0247
	P-value	0.3401	0.4598	0.9948	0.3125	0.9421	0.9763	0.7751	0.1285	0.1842
ISGYO	**Coeff**	-0.0244	-0.0321	-0.0239	0.0258	0.0334	0.0313	-0.0068	-0.0217	-0.0057
	P-value	0.0300	0.0005	0.0406	0.0218	0.0002	0.0070	0.5486	0.0183	0.6245
IZMDC	**Coeff**	-0.0022	-0.0067	0.0048	0.0606	0.0498	0.0686	0.0421	-0.0151	0.0420
	P-value	0.8973	0.6685	0.7789	0.0004	0.0011	0.0000	0.0150	0.3252	0.0135
KARSN	**Coeff**	-0.0533	-0.0475	-0.0026	0.0298	0.1387	0.0806	0.0641	0.0665	0.1363
	P-value	0.0714	0.2076	0.9318	0.3009	0.0002	0.0067	0.0260	0.0797	0.0000
KARTN	**Coeff**	-0.0247	-0.0086	-0.0134	0.0531	0.1245	0.0924	0.0605	0.0079	0.0938
	P-value	0.1117	0.6653	0.4518	0.0005	0.0000	0.0000	0.0001	0.6876	0.0000

TABLE A.1 (CONTINUED): Coefficients and P-values of β of search volume (SV) in individual regressions

KCHOL	**Coeff**	0.0275	0.0192	0.0300	-0.0131	-0.0299	-0.0180	-0.0047	0.0064	-0.0090
	P-value	0.1771	0.2691	0.1827	0.5112	0.0847	0.4156	0.8153	0.7080	0.6850
KIPA	**Coeff**	0.0154	-0.0216	-0.0311	-0.0052	-0.0413	-0.0510	-0.0221	-0.0349	-0.0669
	P-value	0.6226	0.6261	0.4414	0.8680	0.3515	0.2073	0.4792	0.4344	0.0943
KONYA	**Coeff**	-0.0093	0.0210	-0.0482	0.0152	0.0956	0.0342	0.0049	-0.0411	-0.0067
	P-value	0.7094	0.6735	0.3165	0.5412	0.0514	0.4753	0.8464	0.4067	0.8900
KORDS	**Coeff**	-0.0226	-0.0252	-0.0363	0.0208	0.0437	0.0227	0.0052	-0.0159	0.0007
	P-value	0.1190	0.0839	0.0261	0.1510	0.0025	0.1666	0.7226	0.2785	0.9680
KOZAA	**Coeff**	0.1747	0.1244	0.1577	0.1776	0.1383	0.2068	0.1484	0.1539	0.1957
	P-value	0.0011	0.1784	0.0326	0.0002	0.1395	0.0028	0.0017	0.0843	0.0038
KOZAL	**Coeff**	0.0470	-0.0279	0.0178	0.0567	0.0158	0.0174	0.0526	-0.0085	0.0070
	P-value	0.1547	0.5044	0.6467	0.0843	0.7006	0.6546	0.1127	0.8368	0.8591
KRDMD	**Coeff**	-0.0174	-0.1158	-0.0457	0.0212	0.1239	0.0757	0.0218	-0.0001	0.0671
	P-value	0.3224	0.0002	0.1508	0.2222	0.0001	0.0157	0.2120	0.9986	0.0380
KRONT	**Coeff**	0.0484	0.0233	0.0353	0.1717	0.3440	0.3228	0.1225	-0.1398	0.1719
	P-value	0.0867	0.6233	0.4150	0.0000	0.0000	0.0000	0.0000	0.0027	0.0001
LOGO	**Coeff**	-0.0282	-0.0144	-0.0065	0.0150	0.1297	0.1091	0.0187	0.0117	0.1145
	P-value	0.4900	0.8383	0.9281	0.7142	0.0661	0.1298	0.6476	0.8693	0.1095
MAVI	**Coeff**	-0.1754	0.0556	0.0098	-0.1713	-0.0157	0.0482	-0.1922	0.4077	0.2698
	P-value	0.2085	0.7863	0.9650	0.2035	0.9414	0.7717	0.4205	0.1245	0.1320
METRO	**Coeff**	-0.0442	-0.0488	-0.0857	-0.0406	0.0093	-0.0668	-0.0535	-0.0328	-0.0771
	P-value	0.1619	0.3362	0.0358	0.1992	0.8557	0.1038	0.0915	0.5206	0.0591
MGROS	**Coeff**	-0.0111	-0.0266	0.0030	0.0042	0.0118	0.0150	0.0398	0.0265	0.0538
	P-value	0.6722	0.2416	0.9128	0.8761	0.6118	0.5759	0.1445	0.2609	0.0459
NETAS	**Coeff**	-0.0258	0.0127	-0.0012	0.1278	0.1913	0.1921	0.1082	-0.0254	0.1679
	P-value	0.3353	0.6758	0.9668	0.0000	0.0000	0.0000	0.0000	0.3990	0.0000
NTTUR	**Coeff**	0.0003	0.0103	0.0042	0.0557	0.0520	0.0750	0.0226	-0.0305	0.0250
	P-value	0.9851	0.5178	0.8245	0.0007	0.0011	0.0000	0.1748	0.0585	0.1827
ODAS	**Coeff**	-0.0139	-0.0053	0.0121	0.0290	0.0486	0.0611	0.0632	0.0373	0.0960
	P-value	0.5791	0.8417	0.6667	0.2467	0.0676	0.0280	0.0116	0.1626	0.0006
OTKAR	**Coeff**	-0.0157	-0.0239	0.0171	0.0154	0.0517	0.0657	0.0260	0.0172	0.0717
	P-value	0.3956	0.3113	0.4655	0.4019	0.0290	0.0047	0.1602	0.4678	0.0020
PETKM	**Coeff**	0.0193	-0.0001	0.0037	0.0244	0.0122	0.0291	0.0121	-0.0226	-0.0108
	P-value	0.2798	0.9979	0.9030	0.1615	0.6252	0.3278	0.4917	0.3645	0.7168
PGSUS	**Coeff**	-0.0178	-0.0271	-0.0021	0.0147	0.0427	0.0402	-0.0101	-0.0336	0.0073
	P-value	0.3884	0.2536	0.9322	0.4695	0.0680	0.0923	0.6188	0.1548	0.7613
PRKME	**Coeff**	0.0037	-0.0416	-0.0383	0.0534	0.0998	0.0576	0.0975	0.0834	0.1256
	P-value	0.8876	0.2576	0.2618	0.0361	0.0054	0.0856	0.0001	0.0198	0.0002

TABLE A.1 (CONTINUED): Coefficients and P-values of β of search volume (SV) in individual regressions

SAHOL	**Coeff**	-0.0047	0.0016	-0.0050	-0.0030	0.0016	0.0008	-0.0198	-0.0164	-0.0258
	P-value	0.7583	0.9167	0.7654	0.8413	0.9155	0.9612	0.1898	0.2787	0.1207
SASA	**Coeff**	0.0346	-0.0558	0.0063	0.1007	0.2690	0.1598	0.1391	0.1660	0.2609
	P-value	0.2840	0.3806	0.8995	0.0014	0.0000	0.0011	0.0000	0.0088	0.0000
SISE	**Coeff**	0.0100	-0.0187	-0.0076	0.0070	-0.0238	-0.0299	0.0083	0.0112	-0.0199
	P-value	0.3893	0.5746	0.8181	0.5437	0.4707	0.3555	0.4744	0.7374	0.5378
SODA	**Coeff**	-0.0016	0.0090	0.0182	0.0019	0.0845	0.0530	-0.0003	-0.0609	0.0052
	P-value	0.8584	0.8391	0.5757	0.8354	0.0571	0.1021	0.9741	0.1691	0.8735
TATGD	**Coeff**	-0.0018	-0.0286	-0.0063	0.0267	0.0459	0.0398	0.0171	-0.0186	0.0117
	P-value	0.9275	0.2566	0.8291	0.1759	0.0665	0.1565	0.3883	0.4590	0.6777
TAVHL	**Coeff**	-0.0018	-0.0192	-0.0310	0.0052	0.0114	-0.0085	-0.0081	-0.0218	-0.0335
	P-value	0.9068	0.3163	0.2032	0.7301	0.5536	0.7276	0.5910	0.2591	0.1743
TCELL	**Coeff**	-0.0026	-0.0130	-0.0289	0.0243	0.0312	0.0159	0.0127	-0.0136	-0.0026
	P-value	0.8664	0.4401	0.1057	0.1195	0.0629	0.3750	0.4231	0.4194	0.8855
THYAO	**Coeff**	-0.0027	-0.0550	-0.0172	0.0015	0.0221	0.0093	-0.0035	-0.0224	-0.0237
	P-value	0.8324	0.0583	0.5906	0.9053	0.4508	0.7710	0.7828	0.4401	0.4555
TKFEN	**Coeff**	0.0279	-0.0003	0.0047	0.0233	-0.0050	-0.0020	0.0081	-0.0176	-0.0319
	P-value	0.0485	0.9864	0.7839	0.0994	0.7368	0.9057	0.5787	0.2416	0.0595
TKNSA	**Coeff**	-0.0026	0.0204	-0.0096	0.0086	0.0131	0.0146	-0.0053	-0.0164	-0.0053
	P-value	0.8948	0.3475	0.7011	0.6662	0.5428	0.5524	0.7904	0.4453	0.8297
TMSN	**Coeff**	-0.0382	-0.0590	-0.0185	0.0675	0.2232	0.1399	0.0667	-0.0017	0.1362
	P-value	0.0442	0.0359	0.4051	0.0004	0.0000	0.0000	0.0004	0.9525	0.0000
TOASO	**Coeff**	-0.0010	0.0013	-0.0093	0.0092	0.0098	0.0029	-0.0039	-0.0130	-0.0172
	P-value	0.9416	0.9243	0.5625	0.5126	0.4753	0.8563	0.7839	0.3437	0.2820
TRCAS	**Coeff**	-0.0146	-0.0008	-0.0008	0.0329	0.0378	0.0453	0.0322	-0.0014	0.0399
	P-value	0.3286	0.9515	0.9582	0.0262	0.0042	0.0028	0.0293	0.9148	0.0080
TRGYO	**Coeff**	-0.0167	-0.0014	0.0016	0.0352	0.0317	0.0532	0.0395	0.0021	0.0421
	P-value	0.3551	0.9238	0.9247	0.0505	0.0239	0.0018	0.0293	0.8803	0.0142
TRKCM	**Coeff**	-0.0071	-0.0063	-0.0249	0.0158	0.0237	0.0070	0.0177	0.0016	0.0187
	P-value	0.5726	0.6231	0.1087	0.2090	0.0634	0.6485	0.1621	0.9019	0.2261
TSKB	**Coeff**	-0.0065	-0.0089	-0.0188	-0.0091	-0.0022	-0.0121	0.0224	0.0254	0.0317
	P-value	0.7135	0.5767	0.3560	0.6034	0.8904	0.5499	0.2045	0.1109	0.1157
TSPOR	**Coeff**	-0.0392	0.0204	-0.0393	0.0860	0.2610	0.1630	0.1158	0.0628	0.2089
	P-value	0.1358	0.6011	0.2300	0.0011	0.0000	0.0000	0.0000	0.0987	0.0000
TTKOM	**Coeff**	-0.0024	0.0010	-0.0068	0.0299	0.0286	0.0317	0.0103	-0.0180	0.0031
	P-value	0.8541	0.9395	0.6396	0.0224	0.0203	0.0293	0.4434	0.1476	0.8329

TABLE A.1 (CONTINUED): Coefficients and P-values of β of search volume (SV) in individual regressions

TTRAK	**Coeff**	0.0064	-0.0107	0.0023	0.0244	0.0190	0.0169	0.0048	-0.0205	-0.0111
	P-value	0.6514	0.4627	0.8863	0.0850	0.1920	0.2904	0.7380	0.1574	0.4879
TUPRS	**Coeff**	0.0052	-0.0023	-0.0121	0.0121	0.0128	0.0108	-0.0090	-0.0369	-0.0267
	P-value	0.6950	0.8950	0.5414	0.3465	0.4550	0.5738	0.4879	0.0298	0.1642
ULKER	**Coeff**	-0.0237	-0.0548	-0.0104	-0.0140	0.0095	-0.0045	-0.0097	0.0050	-0.0050
	P-value	0.5193	0.1338	0.7782	0.7015	0.7954	0.9025	0.7907	0.8909	0.8919
VAKBN	**Coeff**	-0.0063	0.0062	-0.0141	0.0077	0.0096	-0.0001	-0.0234	-0.0215	-0.0296
	P-value	0.7457	0.7008	0.4800	0.6914	0.5512	0.9946	0.2298	0.1837	0.1393
VESBE	**Coeff**	-0.0272	-0.0160	-0.0158	0.0743	0.1537	0.1332	0.0532	-0.0324	0.0910
	P-value	0.1920	0.5371	0.5362	0.0003	0.0000	0.0000	0.0106	0.2065	0.0003
VESTL	**Coeff**	-0.0394	-0.0255	0.0050	0.0993	0.1659	0.1599	0.0836	-0.0196	0.1356
	P-value	0.2039	0.4513	0.8854	0.0011	0.0000	0.0000	0.0067	0.5634	0.0001
VKGYO	**Coeff**	-0.0555	-0.0270	-0.0171	-0.0658	-0.0145	-0.0317	-0.0169	0.0718	0.0089
	P-value	0.0773	0.4838	0.6054	0.0366	0.7046	0.3368	0.5911	0.0610	0.7869
YATAS	**Coeff**	0.0558	0.0407	0.0063	0.0902	0.0589	0.0754	0.0653	-0.0285	0.0119
	P-value	0.0286	0.2276	0.8583	0.0004	0.0821	0.0315	0.0085	0.3889	0.7271
YAZIC	**Coeff**	0.0108	-0.0201	0.0092	0.0633	0.0351	0.0527	0.0102	-0.0362	-0.0007
	P-value	0.5721	0.2037	0.6220	0.0009	0.0257	0.0043	0.5968	0.0221	0.9696
YKBNK	**Coeff**	0.0278	0.0015	0.0010	0.0264	-0.0013	0.0003	0.0032	-0.0209	-0.0327
	P-value	0.1710	0.9391	0.9656	0.1938	0.9477	0.9899	0.8756	0.2831	0.1754
ZOREN	**Coeff**	-0.0074	0.0148	0.0227	0.0653	0.2000	0.1874	0.0774	0.0448	0.2022
	P-value	0.7144	0.6571	0.4651	0.0009	0.0000	0.0000	0.0001	0.1778	0.0000

Note: Coefficients and P-values of beta (β) of SV in individual regressions in equation **(4.1)**. First column represents stock ticker symbols. First row represents time in which Google search volumes are obtained. At time t-1, search volumes for t-1 is regressed on returns of t. At time t, search volumes for t is regressed on returns of t. At t+1, search volumes for t+1 is regressed on returns of t. Second row includes models that are used to modify search volume. Model 1 is the search volume in its original form provided by Google Trends (SV_{t-1} or SV_t, or SV_{t+1} according to the time). Model 2 is difference in search volume from last week to current week ($SV_{t-1} - SV_{t-2}$ or $SV_t - SV_{t-1}$ or $SV_{t+1} - SV_t$ according to the time). Model 3 is the increase in search volume from median of the last 7 weeks to the current week (SV_{t-1} – Median(SV_{t-2}, SV_{t-3},…,SV_{t-8}) or SV_t – Median(SV_{t-1}, SV_{t-2},…,SV_{t-7}) or SV_{t+1} – Median(SV_t, SV_{t-1},…,SV_{t-6})).

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