Does Google Search Data Provide Information About Current and Future Stock Behaviour?

A study on how Google searches relate to stock returns, liquidity and volatility

***

Nils Hemmingsson* & Jakob Gip Orreborn†

Bachelor's Thesis
Department of Finance
Stockholm School of Economics

May 2016

Abstract

This study investigates the relation between Google searches and current and future stock behaviour. Google Inc. provides a service named Google Trends which makes collection of Google search frequency data possible. With respect to this data, an Abnormal Search Volume Index ($ASVI_{i,t}$) was defined, and its relation with abnormal returns, abnormal liquidity and abnormal volatility was studied. Furthermore, to broaden previous research, a larger number of companies was used, including companies listed on S&P 500 and S&P 350 Europe. Moreover, potential geographical differences were examined, and both ticker name and company name as search queries were used. It was found that current high values of $ASVI_{i,t}$ correlate positively with all dependent variables, except for abnormal returns for European stocks. This suggests that Internet usage is different when investors study European and American stocks. Furthermore, lagged dependent variables were incorporated. The results varied, but with regards to abnormal returns, it was found that, following high values of $ASVI_{i,t}$, the abnormal returns correlate negatively, thus confirming the theory of sentiment-induced mispricing.

Keywords: Google searches, abnormality, returns, liquidity, volatility

Tutor: Irina Zviadadze

Acknolegdements: We would like to thank our tutor Irina Zviadadze for providing us worthful information and guidance. Moreover we would also like to thank Laurent Bach for valuable lectures on the way to our final product. All errors are on behalf of our mistakes.

*23028@student.hhs.se
†22858@student.hhs.se

Contents

1 Introduction

The ability to predict the stock market and the understanding of factors causing stock movements are two key areas within financial research. One factor that is believed to possess predictive power, due to its relation to stocks' behavior, is investor attention. Several studies have been conducted within this area, and a problem that reappears is often what suitable proxies there are for investor attention. Following from the intense technological development during the last three decades, Internet has made financial information more accessible to a larger group of investors and search engines have been shown to be useful in the search for such information. As Internet has become one of the major tools for finding financial information, a large part of investor attention could be considered as being attributable to online searches. Hence, statistics on investors' online search behavior have been suggested as a more direct and precise measure for investor attention, enabling further development of the understanding of the relation between attention grabbing stocks and their behavior.

Since Google Inc. in 2004 launched a service where one can find search frequency for certain search queries, a new tool for monitoring investors' attention has become available. Research on this subject has been made on a number of companies, and studies have shown that Google search frequency has great potential acting as a proxy for investor attention. Furthermore, the results have pointed out that it seems to be a clear relation between Google search intensity and stock behavior. This relation does not only shed light upon the believed link between investor attention and stocks' behavior, but does also contribute to the research about the predictability of the stock market. Since previous studies suggest an existing relation between investor attention and stock behavior, and support the use of Google search frequency as a proxy for the former, a natural next step would be to further generalize these findings. Therefore, this thesis wishes to put these previous results in a broader context, and thereby investigate the extent to which the discovered relations may be generalized.

1.1 Aim & Research Questions

This study aims to test if previous findings related to the relation between Google search frequency and stock markets can be generalized to a larger market. Furthermore, we seek to investigate potential geographical differences and the effect of different search queries on the predictive power of Google search frequency when predicting future stock returns, volatility and trading volume. In order to meet this, the study will seek answer to the following research questions:

1. *What is the relation between abnormal Google search volume and abnormal stock return?*
2. *What is the relation between abnormal Google search volume and abnormal volatility?*
3. *What is the relation between abnormal Google search volume and abnormal trading volume?*
4. *Is the relation between Google searches and the studied variables the same for North American and European stocks?*
5. *Are the same results obtained regardless if the used search query is ticker name or company name?*

2 Previous Research

This section presents the previous research that has been carried out within the area of study. The covered papers provide important insights about the relation between investor attention and stock markets as well as suggested proxies for measuring investor attention, thereby constituting the academic foundation upon which our study is developed.

The foundation of this study is based on the connection between investor attention and the behaviour of the stock market. Merton (1987) examined information asymmetry and investor attention and its implications on stock markets. It was found that temporary increase in investor attention generally increases trading volume and stock returns.

The difficulty to find a good and useful proxy for investor attention has led to multiple studies attempting different methods to do so. Gervais et al. (2001) used trading volume as a proxy for investor attention in order to study the stock movements proceeding high values of the former. Furthermore studied proxies for investor attention have for instance been high values of product market advertising (Grullon et al., 2004, Chemmanur & Yan, 2009), front page articles about the stock market and record-breaking events of the Dow index (Yuan, 2008) and high trading volume and extreme returns (Li et al., 2011).

Joseph et al. (2011) studied the validity of online ticker searches as a proxy for investor sentiment. Investor sentiment is defined as *a set of beliefs about cash flows and investment risks that are not necessarily justified by the facts at hand*. Investor sentiment can thereby be seen as a form of investor attention, thus providing useful insights for this thesis. The research finds that online ticker searches can reliably predict abnormal trading volumes and stock returns. The relation between searches and abnormal stock returns are found to be stronger for stocks that are more difficult to arbitrage, i.e. highly volatile stocks.

The hypothesis that individual investors are net buyers rather (buy rather than sell) intention grabbing stocks was confirmed by Barber & Odean (2007). The authors used among others presence in the news, high abnormal trading volume and extreme one-day returns as proxies for investor attention. The hypothesis under study originates from the difficulty individual investors have choosing stocks among the high number of stocks they can potentially buy. This is argued not to be the case when selling, since investors in this case sell stocks they already have.

The usage of search frequency in Google as a new and direct measure of investor attention was examined by Da et al. (2011). They established that Google Search Volume Index (SVI) in a more direct way than other suggested measures captures investor's attention. The authors also claim that the use of ticker names as the main search query acts as a tool for filtering away searches done by non-investors. The findings of SVI as a proxy for investor attention provides a foundation for further research about the relation between investor attention and stock returns.

What's more, Baker and Wurgler (2006, 2007) provided a cross-sectional evidence for sentiment-induced mispricing. It explains how negative sentiment can predict positive abnormal returns in the future, and how positive sentiment today can predict negative subsequent abnormal returns. Da et al. (2014) also found this relation studying *Financial and Economic Attitudes Revealed by Search* (FEARS) relation with stock returns.

Li-Jun et al. (2008) showed that there is buying behaviour differences between Canada and China, giving that buying difference may be present based on different geographical areas. What's more, Coval (2001) found that fund managers make significantly abnormal returns in geographically nearby investments. Thereby, although not directly transmittable to our study, this can provide some explanation to the potential geographical differences between USA and Europe.

3 Theoretical Framework & Hypotheses

This section aims to present the theoretical framework used in the thesis. Beyond of that, our hypotheses for the research are presented.

3.1 Search volumes as a proxy for investor attention

We believe Google's Search Volume Index (SVI) to be a useful predictor of investor attention, and thereby stock movement. Google provides the biggest and most used search engine available on Internet, with a lot more than half of the concerned market[1]. Joseph et al. (2011) found that online searches was a valid proxy for investor attention, and since Google has a large market share, we believe that its searches approximately mirror the searches on the entire search engine market, thus resulting in a good proxy. Furthermore the studies performed by Barber & Odean (2007) and Merton (1987) provide explanation of how this investor attention translates into

[1] Source: Net Applications Inc. https://www.netmarketshare.com, 2016-05-13

stock market movements. Since the previous studies have been performed examining ticker searches, and have found a positive relation, this relation is believed to be bigger and stronger than that of company name searches. Publication bias may be an explanation as to why, to our knowledge, no studies have been performed presenting significant relation between company name searches and stock market returns. However, *Can Google Search Volume Data Help Predict Future Stock Measures?* was produced by Lundstrm & Nestius (2012), two students at Stockholm School of Economics who found a positive relation between Search Volume Index and stock returns for companies listed on OMX Nordic.

3.2 Abnormality instead of absolute magnitudes

In the investigation of the relation between search behavior and stock characteristics, we have chosen to employ abnormal deviations of the concerned variables instead of their absolute values. Hence, the study seeks to find out to what extent abnormal increases and decreases in stock return, volatility and liquidity are correlated with abnormal Google search frequencies. In the following section a brief explanation will be given on the used approaches for measuring abnormality.

To begin with, abnormal Google search frequencies are measured using two approaches; a mean-approach and a median-approach. The difference between the two approaches lies within the estimators for expected search frequencies. The mean-approach uses the mean value of prior observations as an estimator for the expected value, whereas the median approach employs the median for estimating the expected values. Even though previous research seems to often employ the median-approach - e.g. Da et al. (2011) estimates expected search volume using the median - it was desirable to investigate the impact of using the mean approach. There are advantages and disadvantages with both methods; the median-approach is normally better if outliers are present, whereas the mean-approach usually provides a better measure if not. Thus, by including the mean-approach as a complement to the median-approach, we believe that more robust results can be obtained.

When it comes to the abnormal returns, these are derived using the CAPM formula. Each expected return is thus calculated as the market excess return amplified with its corresponding firm beta, where each firm's beta has been estimated through regression over the entire data set (see section 4.4.2). The S&P 500 and S&P 350 Europe indices are used as proxies for the US and European market returns. Moreover, the US and European risk-free interest rates are, respectively, proxied with 3-months US and UK Treasury Bills. Abnormal volatility and abnormal liquidity are both obtained using the mean of previous observations as an estimator for the expected values.

The median and mean calculations are, for all variables, based on a window covering the eight preceding weeks. Explicit definitions and further explanations of the variables are provided in section 4.4.

3.3 Geographical differences

There exist multiple differences between USA and Europe; cultural, social, political and many more. Thereby potential differences in buying and Internet behaviour could be present. Furthermore, Coval (2001), as mentioned above, found that geographical nearby investments on average have higher returns. Since the US stock market is bigger than the European, and thereby likely more attention grabbing, it can be argued that European investors on a bigger scale invest in both the European and the American market, whereas US investors only invest in the American stock market. If this is the case, the relation between abnormal returns and online searches would be found to be stronger on European stocks. However, we do not believe this phenomenon to be sufficiently apparent.

3.4 Hypotheses

In light of the previous research and the theoretical framework, we believe that Google searches function as a good proxy for investor attention. Furthermore it is hypothesized that abnormal search volumes can predict abnormal returns, abnormal trading volume and abnormal volatility. Henceforth, we believe ticker name searches to be better predictors of investor attention than firm name searches, but the latter is believed to be a useful proxy for investor attention as well. Lastly, geographical differences between North American and European stocks are not believed to be notably present.

4 Data & Methodology

4.1 Data collection

Search Volume Index

Google Inc. provides a service named Google Trends, where one searches for terms, and get their search statistics from 2004 up until two days ago. The previous three months, daily statistics are available. Prior to that, only weekly statistics are as of now published. For the thesis, weekly statistics will thereby be used. The time interval for the thesis is 2005-2015. The data for 2004 is excluded, since it was found to be very volatile. This is in line with Da et al. (2011), where the data for 2004 was excluded for the same reason. The data is based on world-wide searches, and is not geographically restricted to the studied areas. This gives that regarding the potential geographical differences, the research focuses on potential differences in searching behaviour regarding European and American stocks rather than looking for behavioural differences in European and American investors. A consequence of this is also that it is possible to receive SVI data for more number of companies.

The statistics are presented in terms of search volume index (SVI). The values are not in absolute numbers, but instead relative, where the highest value in the search period being studied is put to 100. The index also takes increasing total search volume into account. The number of internet users is steadily increasing and to account for this, the SVI is weighted, so one can study relative increases rather than absolute. Data are only available for search queries which have sufficient search volume for the concerned time frame. Thereby, some company name or ticker name searches will lead to missing values, thus being removed from the sample.

When one searches for a company name, it is likely that one as a search query uses the way the company is communicated in common language. We have therefore modified the company names, taking this into account. Thereby, for instance the company name *Apple Inc* has been altered to *Apple*. The data for search queries as *Apple* are likely to both include searches with the objective to find the fruit apple and the company Apple Inc. whereas the data for *AAPL* are likely to almost exclusively included searches regarding the company, and more specifically the stock of it. This is intended, and provides further reason to believe that the SVI for ticker names provide more predictive power than company names.

We wrote a programming script with the function of collecting Google Trends data in the programming language *R*. The program receives a list of search queries, one for ticker names and one for company names, and outputs the Search Volume Index for the concerned period. If this wouldn't have been done, the data collection process would have been extremely time consuming. By writing the program, we were able to perform the study on a very big sample and to test both ticker and company name as search queries, something that otherwise would have been practically impossible given the time frame of the thesis.

Stock Price Indices

In order to conduct the analysis, data for stock prices and trading volumes are collected. The data used consist of weekly observations during the period January 2005 - December 2015 for all companies included in the S&P 500 and S&P 350 Europe indices. A weekly frequency is employed due to Google's search volume data being provided as weekly data. Moreover, since the two indices continuously change the set of firms included, the list of firms communicated by the end of March 2016 is used for all data collection and firms having missing data in the concerned time period are dropped. The stock market data, VIX and 3-months UK and US Treasury Bonds, which are used as a proxy for the risk-free rate, are collected from *Thomsom DataStream*.

4.2 Division of Datasets

In order to maintain big datasets and in turn receive reliable results, the datasets have been divided into different subdatasets. First off, we have separated the datasets with regards to company name searches and ticker searches. The reason for this is that otherwise we would need SVI data for both of these for the same companies, as well as stock market data. This would likely lead to a lot of missing values, thereby decreasing the scope of the dataset. However, this results in that we can't test the significance between the predictive power of the two queries. On the other hand, results for the two of them will likely be more precise, and discussions can be made thereafter.

Furthermore, the dataset has been divided with regards to what relation with the search volume index is ought to be studied. Thereby, two datasets are received for each abnormality (returns, liquidity and volatility), one for company names and one for ticker names. In result of the division of the data set, six datasets are received.

4.3 Descriptive statistics

Table 1 shows descriptive statistics of the data collected based on ticker names. The included variables are the collected ones, whereas descriptive statistics for the calculated variables can be found in section 4.5.

The weekly log returns for the combined sample is found to be around 11.5% and are on average approximately 3 percentage units higher in the US than in Europe. Regarding the standard deviation and min and max values, they are found to be similar in the US and Europe, and thereby also in the combined sample.

		Total Sample	USA	Europe
Weekly Log-Returns	Mean	0.1147%	0.1295%	0.0897%
	Std. Dev.	4.882	4.899	4.854
	Min	-166.1%	-156.5%	-166.1%
	Max	86.35%	86.35%	66.67%
SVI	Mean	44	44	45
	Std. Dev.	23	23	22
	Min	0	0	0
	Max	100	100	100
Sample Size				
	No. of observations	396 516	248 682	147 834
	No. of companies	692	434	258
Liquidity	Mean	32 584	29 538	37 554
	Std. Dev.	87 445	71 995	107 824
	Min	2	7	2
	Max	5 326 739	3 515 351	5 326 739
SVI	Mean	44	44	45
	Std. Dev.	23	23	23
	Min	0	0	0
	Max	100	100	100
Sample Size				
	No. of observations	401 800	249 116	152 684
	No. of companies	700	434	266

Table 1: **Descriptive statistics of Ticker Name Data**
The table presents the descriptive statistics for the data sample with ticker name searches. Weekly Log-Returns is the continious weekly returns, SVI is the Search Volume Index provided by Google Inc. and Liquidity the trading volume for a week.

When having removed the companies that have missing values either in SVI or in the data from *DataStream*, the number of companies is 434 in USA and 258 Europe. Thereby, we find that a relatively higher amount of European companies miss some sort of values over the time period studied.

Regarding the liquidity we find it to be larger in Europe, both in terms of mean values and maximum values. The standard deviation is also higher in Europe. The minimum values were found to be approximately the same, almost reaching values of zero.

The same number of American companies were removed from the sample due to missing values, but a slightly fewer number of European companies were removed when volatility was concerned.

The descriptive statistics for SVI were very similar between both American and European companies, and between the samples used for returns and liquidity. The mean values were all between 44 and 45 and the the variable's standard deviations take values between 22 and 23.

The descriptive statistics for the same variables as above, but using company names instead of ticker names are presented in Table 2. The data is mostly similar to that presented in Table 1, but some differences are present. For instance, the SVI is not as equally distributed, and takes mean values that are approximately 10% lower. Furthermore, a larger number of American companies and a lower number of European companies have been removed from the dataset.

		Total Sample	USA	Europe
Weekly Log-Returns	Mean	0.1166%	0.1308%	0.0962%
	Std. Dev.	4.851	4.864	4.833
	Min	-166.1%	-156.5%	-166.1%
	Max	86.35%	86.35%	66.67%
SVI	Mean	38	36	40
	Std. Dev.	22	22	23
	Min	0	0	0
	Max	100	100	100
Sample Size				
	No. of observations	402 819	237 795	165 024
	No. of companies	703	415	288
Liquidity	Mean	32 560	29 887	36 430
	Std. Dev.	87 392	73 425	104 229
	Min	3	87	3
	Max	5 326 739	3 515 351	5 326 739
SVI	Mean	39	36	40
	Std. Dev.	22	22	23
	Min	0	0	0
	Max	100	100	100
Sample Size				
	No. of observations	401 800	237 636	164 164
	No. of companies	700	414	286

Table 2: **Descriptive Statistics of Company Name Data**
The table presents the descriptive statistics for the data sample with ticker name searches. Weekly Log-Returns is the compounded weekly returns, SVI is the Search Volume Index provided by Google Inc. and Liquidity the trading volume for a week.

In Figure 1 and 2 one can find the Search Volume Index for the search queries *AAPL* and *Apple*. One can deduce that they differ rather substantially, thus making the study between the two qualified.

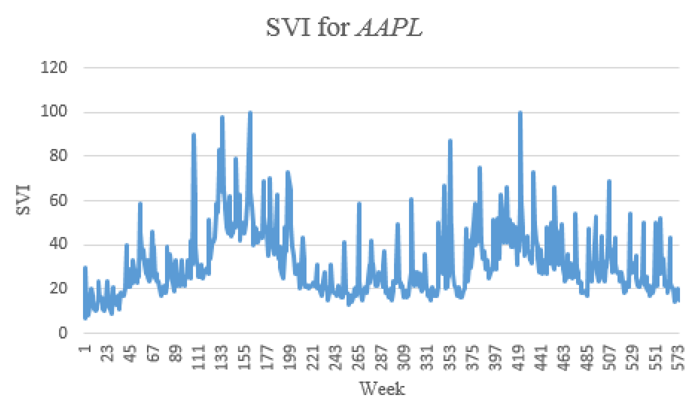

Figure 1: 'AAPL' as query

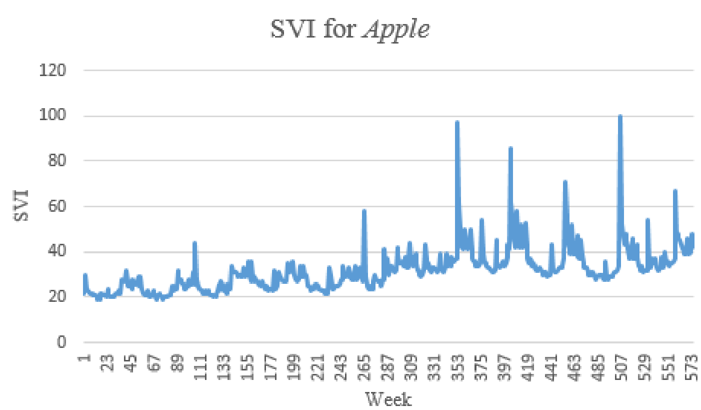

Figure 2: 'Apple' as query

Figure 3: **Google Searvh Volume Index using ticker and name for Apple Inc.**
The graph presents the Search Volume Index provided by Google Inc. over the concerned time period.

4.4 Methodology

In order to test our hypotheses, multiple regressions are performed. First off, the variables of the regressions must be defined.

Abnormal Search Volume Index

The expected value of SVI for company i at time t(measured in weeks), i.e. $E[SVI_{i,t}]$, is defined in two different ways, using both mean values and median values of a number of previous weeks. Using the mean approach, $E[SVI_{i,t}]$ is defined as follows where SVI is the obtained value of Search Volume Index from Google Trends.

$$E[SVI_{i,t}] = \frac{\sum_{j=1}^{n} SVI_{i,t+j-(n+1)}}{n}$$

Where n is the number of weeks prior to t the expected value is based on, and $n = 8$ will be used. The SVI used will vary from including firm names and ticker names. This will enable us testing the results for different search queries.

Using the median approach, the definition is as follows:

$$E[SVI_{i,t}] = Median(SVI_{i,t-1}, SVI_{i,t-2}, ..., SVI_{i,t-(n+1)})$$

In unison with Da et al. we introduce a measurement for relative search magnitude. Abnormal Search Volume Index for company i at time t,$ASVI_{i,t}$ is defined as:

$$ASVI_{i,t} = ln(SVI_{i,t}) - ln(E[SVI_{i,t}])$$

Abnormal returns

The returns for firm i at time t is defined as follows, where $P_{i,t}$ is the price of stock i at time t:

$$r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1})$$

Abnormal returns for firm i at time t is defined as the actual return subtracted by its expected value, i.e.:

$$ar_{i,t} = r_{i,t} - r_{f_{i,t}} - E[r_{i,t} - r_{f_{i,t}}]$$

Thereby, the expected excess returns must be found. This is done by applying the CAPM model. The formula is as follows.

$$r_{i,t} - r_{f_{i,t}} = \alpha_i + \beta_{1_i}(r_{m_{i,t}} - r_{f_{i,t}}) + \epsilon_{i,t}$$

Thus, the expected excess return is

$$E[r_{i,t} - r_{f_{i,t}}] = \beta_{1_i}(r_{m_{i,t}} - r_{f_{i,t}})$$

Abnormal liquidity

In order to test the hypothesis of abnormal search volumes' correlation with abnormal liquidity, the latter must be defined. The definition is based on actual trading volumes, where the natural logarithmic of the actual volume minus the logarithmic of the expected trading volume is used, i.e.:

$$AL_{i,t} = ln(TV_{i,t}) - ln(E[TV_{i,t}])$$

where

$$E[TV_{i,t}] = \frac{\sum_{j=1}^{n} TV_{i,t+j-(n+1)}}{n}$$

Abnormal volatility

Below the abnormal volatility for firm i at time t is defined.

$$AV_{i,t+1} = \sigma_{i,t+1} - E[\sigma_{i,t}]$$

There are different approaches to estimate volatility. Since the objective is to measure the impact of Google searches on volatility, $\sigma_{i,t}$ is based on a window stretching from

t to $t + n_t$:

$$\sigma_{i,t+1} = \sqrt{\sum_{j=0}^{n_t} (r_{i,t+j/5} - \mu)^2}$$

Where

$$\mu = \frac{\sum_{j=0}^{n_t} r_{i,t+j/5}}{n_t + 1}$$

Where $n_t + 1$ is the number of trading days the window is stretching over. $n_t + 1 = 5$ will be used.

The expected value of volatility is defined in a similar way as the previous expected values, i.e.:

$$E[\sigma_{i,t}] = \frac{\sum_{j=1}^{nn} \sigma_{i,t+j-(n+1)}}{n}$$

We will use $n = 8$ for this defintion as well.

4.5 Descriptive Statistics for imposed variables

		Total Sample	USA	Europe
Abnormal Return	Mean	0.04754%	0.04960%	0.04457%
	Std. Dev.	4.311	4.308	4.316
	Min	-170.6%	-157.8%	-170.6%
	Max	85.15%	85.15%	69.21%
ASVI (Median approach)	Mean	-0.0068	-0.0078	-0.0053
	Std. Dev.	0.2227	0.2272	0.2160
	Min	-2.110	-1.981	-2.110
	Max	4.605	4.605	3.912
ASVI (Mean approach)	Mean	-0.0186	-0.0205	-0.0160
	Std. Dev.	0.2264	0.2307	0.2200
	Min	-2.242	-2.118	-2.242
	Max	5.075	5.075	3.594

Table 3: **Descriptive Statistics of Imposed Variables with Company Name and Return Data**
The table presents the descriptive statistics of the imposed variables for the data sample with company name searches. Abnormal Returns is the continious weekly abnormal returns, ASVI is the Abnormal Search Volume Index, which is the observed value minus the expected value, which is the median or mean values of the eight prior weeks.

In Table 3, the descriptive statistics of abnormal returns and ASVI with the dataset using company names are presented. One can see that the mean values of the abnormal returns unsurprisingly hover around zero, but are slighlty positive. They are also slightly larger for American companies. The values of min, max and standard deviation are similar in USA and Europe. Regarding the $ASVI_{i,t}$, the values are of course alike when using the two different approaches of calculating $E[SVI_{i,t}]$. However, it is interesting to find that the mean values of the variable is negative, meaning that on average the decreases are larger in relative magnitude than the increases.

In Table 4 the corresponding table to Table 3, but using ticker names instead of company names is presented. We find that for this dataset, the abnormal returns are on average lower. What's more, the mean values of $ASVI$ for the median approach are all positive in this dataset. Except from that, the statistics are similar.

		Total Sample	USA	Europe
Abnormal Return	Mean	0.0440%	0.04762%	0.03801%
	Std. Dev.	4.335	4.335	4.336
	Min	-170.6%	-157.8%	-170.6%
	Max	85.15%	85.15%	69.21%
ASVI (Median approach)	Mean	0.0039	0.0048	0.0025
	Std. Dev.	0.1894	0.1960	0.1778
	Min	-3.209	-3.209	-1.740
	Max	3.912	3.507	3.912
ASVI (Mean approach)	Mean	-0.0093	-0.0105	-0.0073
	Std. Dev.	0.1913	0.1966	0.1820
	Min	-3.209	-3.209	-1.872
	Max	3.912	3.129	3.912

Table 4: **Descriptive Statistics of Imposed Variables with Ticker Name and Return Data**
The table presents the descriptive statistics of the imposed variables for the data sample with ticker name searches. Abnormal Returns is the continious weekly abnormal returns, ASVI is the Abnormal Search Volume Index, which is the observed value minus the expected value, which is the median or mean values of the eight prior weeks.

In Table 5 and Table 6 the descriptive statistics for the liquidity datasets are presented. The statistics are found to be very similar with the only main difference being that the mean values of $ASVI$ are found to be positive for the median approach and negative for the mean approach when ticker names are concerned, whereas they are negative for both approaches regarding company names. What's more, the standard deviations of $ASVI$ are somewhat larger in the latter case.

		Total Sample	USA	Europe
Abnormal Liquidity	Mean	-0.05281	-0.04640	-0.06208
	Std. Dev.	0.3962	0.3748	0.4252
	Min	-4.466	-1.991	-4.466
	Max	5.971	2.999	5.971
ASVI (Median approach)	Mean	-0.0074	-0.0082	-0.0061
	Std. Dev.	0.2230	0.2276	0.2162
	Min	-2.110	-1.981	-2.110
	Max	4.605	4.605	3.912
ASVI (Mean approach)	Mean	-0.01919	-0.02089	-0.01672
	Std. Dev.	0.2266	0.2311	0.2198
	Min	-2.242	-2.118	-2.242
	Max	5.075	5.075	3.594

Table 5: **Descriptive Statistics of Imposed Variables with Company Name and Liquidity Data**
The table presents the descriptive statistics of the imposed variables for the data sample with company name searches. Abnormal Liquidity is the weekly abnormal trading volume, ASVI is the Abnormal Search Volume Index, which is the observed value minus the expected value, which is the median or mean values of the eight prior weeks.

		Total Sample	USA	Europe
Abnormal Liquidity	Mean	-0.05225	-0.04633	-0.06191
	Std. Dev.	0.3955	0.3753	0.4267
	Min	-4.466	-2.473	-4.466
	Max	5.971	3.917	5.971
ASVI (Median approach)	Mean	0.0038	0.0046	0.0024
	Std. Dev.	0.1898	0.1961	0.1789
	Min	-3.209	-3.209	-1.814
	Max	3.912	3.507	3.912
ASVI (Mean approach)	Mean	-0.009516	-0.01071	-0.007563
	Std. Dev.	0.1917	0.1968	0.1829
	Min	-3.209	-3.209	-1.872
	Max	3.912	3.129	3.912

Table 6: **Descriptive Statistics of Imposed Variables with Ticker Name and Liquidity Data**
The table presents the descriptive statistics of the imposed variables for the data sample with ticker name searches. Abnormal Liquidity is the weekly abnormal trading volume, ASVI is the Abnormal Search Volume Index, which is the observed value minus the expected value, which is the median or mean values of the eight prior weeks.

4.6 Regressions

The relation between excess return and Google Search volume is in the first step studied with help of the following regressions:

$$\begin{aligned} ar_{i,t} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \beta_4 VIX_t + \epsilon_{i,t} \\ ar_{i,t+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \quad (1)$$

where $ASVI_{i,t}$ is the abnormal search volume for company i at time t, I_{Europe_i} is a dummy variable indicating if an observation relates to a European firm, and VIX_t is the Chicago Board Options Exchange's volatility index controlling for various financial factors such as recessions and other economic conditions.

The difference between regressions (1) is that a time lag of s weeks has been added to the dependent variable. Running this regression enables us to investigate if the effect of abnormal search volume on abnormal returns rather takes place with a few weeks delay than during the same week. It is chosen to run the lagged regression for $s = [1, 2, 3, 4, 5]$.

It is worth mentioning that regressions (1) do not control for potential systematic differences between the firms that may posses explanatory power when it comes to explaining abnormal returns. A potential remedy for this phenomenon is to investigate the above regression while controlling for such fixed effects. Hence, the following fixed effects regressions are to be run as a complement to (1):

$$\begin{aligned} ar_{i,t} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \\ ar_{i,t+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

where I_{FirmK_i} is a dummy variable indicating if an observation relates to firm K. Thus, regressions (2) control for firm-fixed effects, and enable us to investigate whether these have an impact on the results or not.

Regarding the relation between abnormal trading volume and $ASVI$, the corresponding regressions to (1) are performed as follows:

$$\begin{aligned} AL_{i,t} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \beta_4 VIX_t + \epsilon_{i,t} \\ AL_{i,t+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

Where s in the same manner as above is the number of lagged weeks used. To further study the relation between $ASVI$ and AL and in order to controll for potential firm fixed effects, the following regressions are performed, beyond of (3):

$$\begin{aligned} AL_{i,t} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \\ AL_{i,t+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 ASVII_{Europe_i} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

What concerns the abnormal volatility, AV, and its relation with $ASVI$ the regression are performed the same fashion as for ar and AL. Their formulas are arranged as follows:

$$\begin{aligned} AV_{i,t+1} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 ASVII_{Europe_i} + \beta_4 VIX_t + \epsilon_{i,t} \\ AV_{i,t+1+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 ASVII_{Europe_i} + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \tag{5}$$

$$\begin{aligned} AV_{i,t+1} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \\ AV_{i,t+1+s} &= \alpha + \beta_1 ASVI_{i,t} + \beta_2 I_{Europe_i} + \beta_3 I_{Europe_i} ASVI_{i,t} + \\ &+ [\gamma_1 ... \gamma_N] \cdot [I_{Firm1} ... I_{FirmN}] + \beta_4 VIX_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

Regressions (1), (3) and (5) are from here on referred to as OLS regressions, and regressions (2), (4) and (6) are referred to as fixed-effects regressions. All regressions are performed using the statistical software STATA; OLS regressions are executed using the command *reg* and fixed-effects regressions using the command *areg*. Moreover, robust standard errors are used for all regressions.

5 Empirical Findings

Abnormal Returns

VARIABLES	OLS ar	Fixed ar	OLS ar	Fixed ar
ASVImean	0.202***	0.201***		
	(0.0491)	(0.0501)		
ASVImeanEurope	-0.342***	-0.325***		
	(0.0785)	(0.0792)		
ASVImedian			0.195***	0.193***
			(0.0501)	(0.0504)
ASVImedianEurope			-0.337***	-0.326***
			(0.0831)	(0.0831)
Constant	0.204***	0.200***	0.201***	0.198***
	(0.0271)	(0.0266)	(0.0271)	(0.0266)
Observations	392,593	392,593	392,145	392,145

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: **Regression Results using Abnormal Returns and Company Names**
The table presents the beta coefficients of the regression studying the relation between abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with company name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

In Table 7 the results of regression (1) using company names is presented. When performing the regression we find that $ASVI_{i,t}$ have positive correlation with abnormal returns on a 1% significance level. This is true for both mean and median approaches when calculating $E[SVI_{i,t}]$ when both regular OLS and fixed effect regression are concerned. Furthermore, we find that the correlation between the concerned variables are substantially different with regards to American and European stocks. The findings are that $ASVI_{i,t}$ has a weaker correlation with abnormal returns when European stocks are concerned rather than American. The finding has a 1% significance level.

VARIABLES	OLS ar	Fixed ar	OLS ar	Fixed ar
ASVImedian			0.284***	0.276***
			(0.0662)	(0.0659)
ASVImedianEurope			-0.386***	-0.382***
			(0.0963)	(0.0960)
ASVImean	0.292***	0.307***		
	(0.0635)	(0.0653)		
ASVImeanEurope	-0.393***	-0.409***		
	(0.0924)	(0.0939)		
Constant	0.207***	0.207***	0.206***	0.203***
	(0.0269)	(0.0269)	(0.0273)	(0.0269)
Observations	389,597	389,597	389,289	389,289

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Regression Results using Abnormal Returns and Ticker Names**
The table presents the beta coefficients of the regression studying the relation between abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with ticker name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

Regarding ticker name searches, one can see the results in Table 8 and deduce that the findings for ticker names are similar to that of company names.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImedian	-0.0892*	-0.000131	-0.0556	-0.226***	-0.142***
	(0.0465)	(0.0463)	(0.0444)	(0.0453)	(0.0455)
ASVImedianEurope	0.0139	-0.0306	0.123	0.0992	-0.0273
	(0.0748)	(0.0759)	(0.0759)	(0.0712)	(0.0706)
Constant	0.0972***	0.0575**	0.0246	0.115***	-0.142***
	(0.0262)	(0.0245)	(0.0236)	(0.0241)	(0.0247)
Observations	392,144	392,143	392,142	392,141	392,140

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: **Regression Results using Lagged Abnormal Returns, Company Names, the Median Approach and OLS**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with company name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImedian	-0.127**	-0.0549	0.00459	-0.150***	0.0194
	(0.0534)	(0.0525)	(0.0500)	(0.0503)	(0.0513)
ASVImedianEurope	0.113	0.0845	-0.0145	0.198**	-0.0339
	(0.0850)	(0.0846)	(0.0842)	(0.0825)	(0.0835)
Constant	0.105***	0.0592**	0.0255	0.121***	-0.145***
	(0.0265)	(0.0247)	(0.0238)	(0.0243)	(0.0249)
Observations	389,288	389,287	389,286	389,285	389,284

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: **Regression Results using Lagged Abnormal Returns, Ticker Names, the Median Approach and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

The results of the lagged version of regression (1) are presented in Table 9 and Table 10. We find that during the weeks following high values of ASVI, the abnormal returns tend to be negative. This is true when using both ticker names and company names, but the concerned weeks differ slightly. Regarding company name searches, the abnormal returns are significantly negative when $s = [1, 4, 5]$ but regarding ticker name searches only when $s = [1, 4]$.

Due to the interesting results that the effect of $ASVI_{i,t}$ where different between American and European stocks, we want to study the correlation between abnormal returns and $ASVI_{i,t}$ only in Europe.

VARIABLES	OLS ar	Fixed ar	OLS ar	Fixed ar
ASVImedian	-0.143**	-0.133**		
	(0.0662)	(0.0661)		
ASVImean			-0.141**	-0.125**
			(0.0612)	(0.0614)
Constant	0.107***	0.107***	0.106**	0.106**
	(0.0414)	(0.0414)	(0.0413)	(0.0413)
Observations	160,621	160,621	160,834	160,834

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 11: **Regression Results using Abnormal Returns and Company Names for European Companies Only**
The table presents the beta coefficients of the regression studying the relation between abnormal returns and the Abnormal Search Volume Index for the data sample with company name searches and only European companies. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

VARIABLES	OLS ar	Fixed ar	OLS ar	Fixed ar
ASVImedian	-0.102	-0.106		
	(0.0699)	(0.0699)		
ASVImean			-0.104	-0.102
			(0.0676)	(0.0676)
Constant	0.108**	0.108**	0.110**	0.110**
	(0.0438)	(0.0438)	(0.0439)	(0.0439)
Observations	144,613	144,613	144,840	144,840

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: **Regression Results using Abnormal Returns and Ticker Names for European Companies Only**
The table presents the beta coefficients of the regression studying the relation between abnormal returns and the Abnormal Search Volume Index for the data sample with ticker name searches and only European companies. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

In Table 11 and Table 12 the relation between $ASVI_{i,t}$ and abnormal returns only in Europe are presented. One can deduce that with regards to company names, $ASVI_{i,t}$ correlates negatively with abnormal returns, on a significance level of 5 %. The correlation is found to be negative with regards to ticker names as well, but not on a significance level as low as 10 %.

Abnormal Liquidity

VARIABLES	OLS AL	Fixed AL	OLS AL	Fixed AL
ASVImean	0.190***	0.190***		
	(0.00435)	(0.00438)		
ASVImeanEurope	-0.0811***	-0.0811***		
	(0.00792)	(0.00793)		
ASVImedian			0.193***	0.195***
			(0.00450)	(0.00451)
ASVImedianEurope			-0.0820***	-0.0833***
			(0.00821)	(0.00820)
Constant	-0.0843***	-0.0906***	-0.0874***	-0.0931***
	(0.00150)	(0.00143)	(0.00150)	(0.00143)
Observations	394,816	394,816	394,508	394,508

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: **Regression Results using Abnormal Liquidity and Ticker Names**
The table presents the beta coefficients of the regression studying the relation between abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

As is shown in Table 13 a positive relation between ASVI and abnormal liquidity is found with regards to ticker searches, on a significance level of 1 %. If $ASVI_{i,t}$ increases with a value of 1, the abnormal liqiudity increases with 16.2%. Furthermore, we find that the relation between $ASVI_{i,t}$ and Trading Volume is stronger for American than European companies. This is true for confidence levels as low as 1%.

VARIABLES	OLS AL	Fixed AL	OLS AL	Fixed AL
ASVImean	0.130***	0.132***		
	(0.00377)	(0.00381)		
ASVImeanEurope	0.132***	0.132***		
	(0.00696)	(0.00699)		
ASVImedian			0.138***	0.139***
			(0.00390)	(0.00391)
ASVImedianEurope			0.133***	0.134***
			(0.00710)	(0.00711)
Constant	-0.0826***	-0.0883***	-0.0843***	-0.0905***
	(0.00151)	(0.00143)	(0.00151)	(0.00143)
Observations	391,632	391,632	391,192	391,192

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: **Regression Results using Abnormal Liquidity and Company Names**
The table presents the beta coefficients of the regression studying the relation between abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

Table 14 shows the relation between $ASVI_{i,t}$ using company names and abnormal liquidity. One can deduce that the result is somewhat weaker than that when using ticker names. Moreover, it is found that the relation between $ASVI_{i,t}$ and Trading Volume is stronger for American than European Companies. This is true for confidence levels as low as 1%.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImedian	0.328***	0.0791***	0.0163***	-0.0213***	-0.0498***
	(0.00513)	(0.00403)	(0.00401)	(0.00400)	(0.00413)
ASVImedianEurope	-0.126***	-0.000471	-0.0132*	-0.000727	0.0180**
	(0.00899)	(0.00765)	(0.00733)	(0.00734)	(0.00740)
Constant	-0.0535***	-0.00882***	0.00748***	0.0142***	0.0300***
	(0.00148)	(0.00152)	(0.00156)	(0.00155)	(0.00166)
Observations	393,809	393,110	392,410	391,710	391,010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: **Regression Results using Lagged Abnormal Liquidity, Ticker Names, the Median Approach and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

In Table 15 the relation between $ASVI_{i,t}$ for ticker names and lagged $AL_{i,t}$ is shown. We see that there is a significant relation between $ASVI_{i,t}$ and $AL_{i,t+s}$ for $s = [1, 2, 3, 4, 5]$, however where the relation is positive for the first three and negative for the last two. The value of the coefficient is highest for $s = 1$, even higher than when no lag is incorporated. The relationship between American and European companies is significantly different for $s = [1, 3, 5]$, showing a weaker correlation for European firms.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImedian	0.288***	0.0914***	0.0295***	-0.0257***	-0.0220***
	(0.00416)	(0.00360)	(0.00354)	(0.00358)	(0.00370)
ASVImedianEurope	0.190***	0.0956***	0.00615	-0.00820	-0.0458***
	(0.00790)	(0.00652)	(0.00626)	(0.00634)	(0.00638)
Constant	-0.0490***	-0.00752***	0.00809***	0.0142***	0.0300***
	(0.00148)	(0.00153)	(0.00158)	(0.00157)	(0.00168)
Observations	390,494	389,795	389,095	388,395	387,695

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: **Regression Results using Lagged Abnormal Liquidity, Company Names, the Median Approach and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with company name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

The relation between $ASVI_{i,t}$ using company names, shown in Table 16, is similar to that when using ticker names. With regards to the differences between European and American companies, the findings are reversed, the relationship is stronger the subsequent weeks and then turns weaker. European companies have a significant positive difference for $s = [1, 2]$ and negative for $s = 5$

Abnormal Volatility

In Table 17 the results of regression 6 using ticker names is presented. We find that there is a significant positive correlation between $ASVI_{i,t}$ and abnormal volatility. Furthermore, the relation is found to be much weaker with regards to European companies. However, it is still positive on a significance level of 1% for European companies

VARIABLES	OLS AV	Fixed AV	OLS AV	Fixed AV
ASVImean	0.0174***	0.0176***		
	(0.000528)	(0.000538)		
ASVImeanEurope	-0.0125***	-0.0126***		
	(0.000647)	(0.000655)		
ASVImedian			0.0166***	0.0167***
			(0.000535)	(0.000537)
ASVImedianEurope			-0.0117***	-0.0117***
			(0.000662)	(0.000663)
Constant	-0.00223***	-0.00227***	-0.00250***	-0.00246***
	(0.000143)	(0.000140)	(0.000143)	(0.000140)
Observations	388,087	388,087	387,818	387,818

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: **Regression Results using Abnormal Volatility and Ticker Names**
The table presents the beta coefficients of the regression studying the relation between abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

The results with regards to abnormal volatility and company names are presented in Table 18. The findings are that there is a positive correlation between $ASVI_{i,t}$ and abnormal volatility, but in this case the relation is stronger for European companies.

VARIABLES	OLS AV	Fixed AV	OLS AV	Fixed AV
ASVImean	0.0109***	0.0111***		
	(0.000357)	(0.000364)		
ASVImeanEurope	0.00227***	0.00219***		
	(0.000509)	(0.000515)		
ASVImedian			0.0111***	0.0111***
			(0.000364)	(0.000367)
ASVImedianEurope			0.00221***	0.00224***
			(0.000541)	(0.000543)
Constant	-0.00213***	-0.00211***	-0.00227***	-0.00226***
	(0.000143)	(0.000140)	(0.000143)	(0.000140)
Observations	384,683	384,683	384,235	384,235

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: **Regression Results using Abnormal Volatility and Company Names**
The table presents the beta coefficients of the regression studying the relation between abnormal volatility and the Abnormal Search Volume Index for the data sample with company name searches. ASVImean is the Abnormal Search Volume Index using the mean values to calculate expected values whereas ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImeanEurope and ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean or ASVImedian. OLS are regular ordinary least squares regressions whereas Fixed are regressions controlling for firm fixed effects.

In Table 19 the relation between lagged volatility and $ASVI_{i,t}$ is presented. One can deduce that the volatility continues to be abnormally high the subsequent weeks of high values of $ASVI_{i,t}$. This is true for the first two weeks, and the three upcoming weeks thereafter, the abnormal volatility is significantly negative. For four of the lagged volatilities, a significant difference between European and American companies is found; the correlation is weaker for $s = [1, 2, 3, 4]$.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImedian	0.00201***	0.00104***	-0.000794***	-0.00231***	-0.00285***
	(0.000283)	(0.000280)	(0.000269)	(0.000285)	(0.000291)
ASVImedianEurope	-0.000476	-0.00137***	0.000345	0.00147***	0.00211***
	(0.000420)	(0.000415)	(0.000412)	(0.000423)	(0.000425)
Constant	0.000570***	0.00268***	0.00421***	0.00535***	0.00565***
	(0.000127)	(0.000124)	(0.000117)	(0.000116)	(0.000117)
Observations	387,130	386,441	385,752	385,063	384,374

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 19: **Regression Results using Lagged Abnormal Volatility Ticker Names, the Median Approach and OLS**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImedian	0.00272***	0.00205***	0.000435*	-0.000204	-0.00131***
	(0.000248)	(0.000247)	(0.000256)	(0.000298)	(0.000262)
ASVImedianEurope	0.00119***	-0.00111***	-0.000929**	-0.00135***	-0.000743*
	(0.000410)	(0.000388)	(0.000385)	(0.000419)	(0.000383)
Constant	0.000607***	0.00267***	0.00415***	0.00526***	0.00554***
	(0.000126)	(0.000125)	(0.000118)	(0.000117)	(0.000118)
Observations	383,547	382,858	382,169	381,480	380,792

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: **Regression Results using Lagged Abnormal Volatility, the Median Approach Company Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with company name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

For company names, the same relation as for ticker names was found between lagged abnormal volatility and $ASVI_{i,t}$ with the exception of the third lagged week. In Table 20 we can see that the abnormal volatility was positive for this week. Furthermore, no significant relation was found for $s = 4$. The difference between European and American stocks was found to be significantly positive for $s = 1$ and significantly negative for $s = [2, 3, 4, 5]$

6 Discussion

In line with the hypotheses posed, it was found that abnormal search volume correlates positively with current abnormal liquidity and volatilty. Moreover, the hypothesis that higher search volumes correlate positively with abnormal returns turned out to be true for non-lagged returns, both when the concerned search query was either ticker names or company names. It is hard to decipher the direction of the causality of the finding regarding current abnormal returns. On the one hand, the situation could be that higher search volume, i.e. increased investor attention, affects prices and not the other way around. Barber & Odean's (2007) findings then suggest that these price impacts would stem from net buying rather than from net selling, implying positive abnormal returns. On the other hand, it can also be the case that positive abnormal returns cause higher search volumes. This would then suggest that it is the positive abnormal returns that yields increased investor attention rather than increased attention leading to higher abnormal returns. In order to further understand this relation we therefore also investigated abnormal search volume's effect on lagged returns.

When regarding the lagged returns, the results are somewhat different than those obtained for simultaneous returns. For the lagged returns, the results show a significant negative correlation for some lags. These findings hence suggest that a boom in investor attention is followed by a decline in abnormal returns. The reason for this behavior likely lies in that attention grabbing stocks are momentarily overhyped, and that the price eventually stabilizes during the weeks following the hype. These findings, indicating that higher SVI today may predict subsequent negative abnormal returns, can be connected to sentiment-induced mispricing. This is a phenomenon explained and elaborated on by Baker and Wurgler (2006,2007), saying that positive sentiments today can predict subsequent negative abnormal returns. This idea connected to Google searches was also used and confirmed by Da et al. (2015).

In contrast to the stated hypothesis, multiple geographical differences were found between American and European stocks. Most notably was the finding that, with regards to American stocks, Google searches correlate positively with abnormal returns, whereas for European stocks there is a negative correlation. Thus, in the case of European stock returns, the results are not in line with the findings presented by Barber & Odean (2007). They stated that investor attention leads to net buying rather than net selling, whereas our results for European stocks suggest that increased investor attention yields negative abnormal stock returns (i.e. net selling rather than net buying). Hence, our results indicate that there might be a difference in Internet usage between investors following American and European stocks.

Investor attention given to European stocks could to a larger extent be seen as information-seeking related to both potential buys and sells, whereas in the case of American stocks the attention is more 'buy-oriented'. As is mentioned, these results regard differences between investors monitoring European stocks and those studying American ones, and therefore not necessarily differences between European and American investors. This follows from the fact that the collection of Google search frequencies have not been geographically restricted, but is based on global search volume. Thus, in order to further develop the understanding of potential geographical differences, studying the geographically restricted search frequencies would be an interesting next step.

The results for the relation between abnormal search volume and abnormal liquidity are coherent with the ones obtained for abnormal returns. Our findings suggest that attention grabbing stocks experience higher abnormal liquidity, which can be connected to the simultaneous increase and subsequent decrease in abnormal returns. Whether the effect of increased investor attention is net buying or net selling, the found price fluctuations following from abnormal search volumes are likely to partly be due to increased trading of the stock.

Regarding the lagged abnormal liquidity, the positive correlation was reduced and eventually became negative. These results can potentially be explained by our definition of abnormality. Since the abnormal liquidity with lag s, i.e. $AL_{i,t+s}$, is based on the previous eight observations, it is substanially effected by the values of these observations. The strong positive correlation for $s = 0$ and $s = 1$ means that the values of $AL_{i,t}$ and $AL_{i,t+1}$ are high. Hence, the mean values, used for calculating subsequent abnormal liquidities, are potentially higher than the correct expected values. This gives that the subsequent abnormal liquidities might be lower than the 'true' values. This scenario is also likely to be applicable to lagged abnormal volatility, since these share the same formula for defining abnormality and have similar results. A drawback of this study can therefore potentially be the definition of abnormality for some of the dependent variables. Since they are based on values from the previous weeks, the examination of lagged variables might become slightly biased. Thus, future studies on this subject are suggested to test other definitions of the studied variables and thereby eliminate potential bias.

We found that the relation between $ASVI_{i,t}$ for company names and abnormal liquidity is stronger for American companies at a significance level of 1%, whereas the opposite holds for ticker names. Thus, it is also likely that there is a statistical difference between the correlations of ticker and company name searches with abnormal liquidity on significance levels of 1 %, since the sample is mostly consisting of the same companies, and the time period is the same.

Regarding the robustness of the conducted study, we performed several robustness checks. Firstly, two measures of the expected value of SVI were applied; the mean and the median approach. The two methods gave similar results, indicating that the study is robust in this area and relatively insensitive to which of the two approaches that is used. Furthermore, both regular OLS regressions and Fixed-Effects regressions were run, controlling for potential firm fixed effects. Also in this case the methods gave similar results, and hence the study is robust with regards to firm-fixed effects.

7 Conclusion

The findings of this thesis support the theory that Google searches provide information about current and future stock behavior. Ticker name searches showed to be correlated with several stock measures for a large set of American and European companies. Furthermore, using company names instead of ticker names as search query gave similar results in most cases, indicating that queries can be widened to company names. These findings apply to both abnormal returns, abnormal liquidity and abnormal volatility.

The theory of sentiment-induced mispricing turned out to be applicable for both ticker name and company name searches in the case of abnormal returns, but the phenomenon is more prominent in the case of company names. Moreover, on the contrary to the posed hypothesis, geographical differences were found to be present. These differences were most prominent in the case of abnormal returns, for which different signs of the correlation were found. For European stocks a negative correlation was obtained, whereas for American stocks there was a positive one. Thus, the theory of investor attention leading to net buying, posed and elaborated on by Barber & Odean (2007), turned out to be applicable for American stocks but not for European ones.

As mentioned above, future research could potentially test other definitions of abnormality of the dependent variables and thereby eliminating potential bias. What's more, the findings regarding geographical differences is an area that ought to be studied more. Thereby, we suggest that further research on this subject should be aimed towards studying potential geographical differences in other stock related matters. As was mentioned in the discussion, one could restrict the Google searches to the geographical areas that ought to be studied, enabling to investigate if the found differences stem from the geographical location of the investors rather than that of the companies.

8 References

Baker; M. & Wurgler; J., 2006 Investor Sentiment and the Cross-Section of Stock Returns, *The Journal of Finance*, 4, pp. 1645-1680, Volume LXI

Barber B. M & Odean T, 2007 All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *The Review of Financial Studies*

Chemmanur, T. J. & Yan, A., 2009, Advertising, Attention, and Stock Returns, Working Paper, Boston College and Fordham University,

Coval, J. D.& Moskowitz, T. J., 2001, The Geography of Investment: Informed Trading and Asset Prices, *The Journal of Political Economy*, Number 4, pp. 811-841, Volume 109

Da, Z, Engelberg, J. & Gao, P., 2011, In Search of Attention, *The Journal of Finance*, Number 5, pp. 1461-1499, Volume LXVI

Da, Z, Engelberg, J. & Gao, P., 2014, The Sum of All FEARS: Investor Sentiment and Asset Prices *The Society for Financial Studies*,

Gervais, S, Kaniel, R. & Mingelgrin D. H., 2001, The High-Volume Return Premium, *Journal of Finance*, Number 3, pp. 877-919, Volume LVI

Grullon, G., Kanatas G. & Westonn J. P., 2004, Advertising, Breath of Ownership, and Liquidity, *Review of Financial Studies*, Number 2, pp. 439-461 Volume 17

Ji L., Zhang, Z. & Gou T., 2008 To buy or to sell: cultural differences in stock market decisions based on price trends, *Journal of Behavioural Decision Making*, Number 4, pp. 399-413 Volume 21

Joseph, K, Wintoki, J. & Zhang, Z.,2011, Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search, International Journal of Forecasting, Number 4, pp. 1116-1127, Volume 27

Li, X, Mahani; R. S. & Sandhya, V., 2011, Does Investor Attention Affect Stock Prices, Working Paper, Georgia State University

Lundstrom, C. & Nestius, H., 2012 Can Google Search Volume Data Help Predict Future Stock Measures?, Stockholm School of Economics

Merton, R. C. A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance*, 1987

Yuan, Y., 2008 Attention and Trading, Working Paper, University of Iowa

9 Appendix

9.1 Returns

Ticker

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImean	-0.138***	-0.0573	0.0120	-0.155***	-0.0132
	(0.0517)	(0.0514)	(0.0492)	(0.0497)	(0.0511)
ASVImeanEurope	0.126	0.0799	0.0139	0.218***	0.00931
	(0.0824)	(0.0855)	(0.0803)	(0.0793)	(0.0804)
Constant	0.104***	0.0593**	0.0268	0.119***	-0.144***
	(0.0265)	(0.0247)	(0.0237)	(0.0243)	(0.0249)
Observations	389,596	389,595	389,594	389,593	389,592

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: **Regression Results using Lagged Abnormal Returns, the Mean Approach Ticker Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImean	-0.129**	-0.0476	0.0221	-0.147***	-0.00304
	(0.0521)	(0.0519)	(0.0495)	(0.0498)	(0.0512)
ASVImeanEurope	0.119	0.0726	0.00523	0.212***	0.00266
	(0.0827)	(0.0858)	(0.0806)	(0.0795)	(0.0806)
Constant	0.102***	0.0567**	0.0236	0.116***	-0.147***
	(0.0262)	(0.0243)	(0.0233)	(0.0239)	(0.0246)
Observations	389,596	389,595	389,594	389,593	389,592

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 22: **Regression Results using Lagged Abnormal Returns, the Mean Approach Ticker Names and Fixed Effects**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImedian	-0.136**	-0.0648	-0.00485	-0.160***	0.0102
	(0.0535)	(0.0527)	(0.0502)	(0.0505)	(0.0515)
ASVImedianEurope	0.121	0.0922	-0.00636	0.208**	-0.0257
	(0.0854)	(0.0848)	(0.0843)	(0.0827)	(0.0838)
Constant	0.101***	0.0561**	0.0221	0.117***	-0.148***
	(0.0262)	(0.0243)	(0.0234)	(0.0240)	(0.0246)
Observations	389,288	389,287	389,286	389,285	389,284

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: **Regression Results using Lagged Abnormal Returns, the Median Approach Ticker Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

Name

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImean	-0.0862*	0.0117	-0.0397	-0.214***	-0.144***
	(0.0458)	(0.0454)	(0.0438)	(0.0447)	(0.0444)
ASVImeanEurope	0.0400	-0.0109	0.148**	0.125*	0.00232
	(0.0703)	(0.0707)	(0.0727)	(0.0695)	(0.0688)
Constant	0.0962***	0.0577**	0.0244	0.113***	-0.144***
	(0.0262)	(0.0245)	(0.0236)	(0.0241)	(0.0247)
Observations	392,592	392,591	392,590	392,589	392,588

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: **Regression Results using Lagged Abnormal Returns, the Mean Approach Company Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with company name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImean	-0.0907*	0.00716	-0.0441	-0.221***	-0.149***
	(0.0463)	(0.0462)	(0.0444)	(0.0453)	(0.0451)
ASVImeanEurope	0.0591	0.0112	0.170**	0.147**	0.0240
	(0.0708)	(0.0713)	(0.0732)	(0.0701)	(0.0694)
Constant	0.0955***	0.0560**	0.0232	0.112***	-0.145***
	(0.0258)	(0.0241)	(0.0231)	(0.0236)	(0.0242)
Observations	392,592	392,591	392,590	392,589	392,588

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 25: **Regression Results using Lagged Abnormal Returns, the Mean Approach Company Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with company name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_ar1	(2) lag_ar2	(3) lag_ar3	(4) lag_ar4	(5) lag_ar5
ASVImedian	-0.0925**	-0.00326	-0.0588	-0.231***	-0.146***
	(0.0467)	(0.0466)	(0.0446)	(0.0454)	(0.0458)
ASVImedianEurope	0.0248	-0.0178	0.137*	0.111	-0.0150
	(0.0749)	(0.0761)	(0.0761)	(0.0714)	(0.0709)
Constant	0.0960***	0.0559**	0.0226	0.113***	-0.144***
	(0.0258)	(0.0241)	(0.0231)	(0.0236)	(0.0243)
Observations	392,144	392,143	392,142	392,141	392,140

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 26: **Regression Results using Lagged Abnormal Returns, the Median Approach Company Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal returns, presented in percentages, and the Abnormal Search Volume Index for the data sample with company name searches. lag.arN is the lagged abnormal returns, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

9.2 Liquidity

Ticker

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImean	0.344***	0.101***	0.0371***	-0.00267	-0.0358***
	(0.00506)	(0.00403)	(0.00401)	(0.00398)	(0.00407)
ASVImeanEurope	-0.142***	-0.0154**	-0.0207***	-0.00963	0.00755
	(0.00884)	(0.00753)	(0.00725)	(0.00725)	(0.00728)
Europe	-0.0178***	-0.0160***	-0.0157***	-0.0155***	-0.0147***
	(0.00133)	(0.00134)	(0.00134)	(0.00134)	(0.00134)
VIX	0.000260***	-0.00194***	-0.00275***	-0.00309***	-0.00386***
	(6.44e-05)	(6.68e-05)	(6.89e-05)	(6.85e-05)	(7.49e-05)
Constant	-0.0480***	-0.00734***	0.00792***	0.0141***	0.0294***
	(0.00148)	(0.00152)	(0.00156)	(0.00155)	(0.00166)
Observations	394,117	393,418	392,718	392,018	391,318
R^2	0.022	0.005	0.005	0.006	0.010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 27: **Regression Results using Lagged Abnormal Liquidity, the Mean Approach Ticker Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImean	0.346***	0.101***	0.0359***	-0.00417	-0.0375***
	(0.00510)	(0.00404)	(0.00401)	(0.00398)	(0.00408)
ASVImeanEurope	-0.143***	-0.0147*	-0.0200***	-0.00885	0.00849
	(0.00886)	(0.00755)	(0.00727)	(0.00727)	(0.00731)
Constant	-0.0548***	-0.0134***	0.00197	0.00819***	0.0238***
	(0.00141)	(0.00145)	(0.00149)	(0.00148)	(0.00159)
Observations	394,117	393,418	392,718	392,018	391,318

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: **Regression Results using Lagged Abnormal Liquidity, the Mean Approach Ticker Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImedian	0.330***	0.0801***	0.0170***	-0.0209***	-0.0495***
	(0.00515)	(0.00403)	(0.00402)	(0.00401)	(0.00413)
ASVImedianEurope	-0.128***	-0.00153	-0.0144*	-0.00186	0.0170**
	(0.00898)	(0.00765)	(0.00735)	(0.00736)	(0.00742)
Constant	-0.0591***	-0.0146***	0.00163	0.00836***	0.0244***
	(0.00141)	(0.00145)	(0.00149)	(0.00149)	(0.00159)
Observations	393,809	393,110	392,410	391,710	391,010

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 29: **Regression Results using Lagged Abnormal Liquidity, the Median Approach Ticker Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

Name

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImean	0.289***	0.102***	0.0426***	-0.0119***	-0.00898**
	(0.00415)	(0.00356)	(0.00349)	(0.00349)	(0.00364)
ASVImeanEurope	0.194***	0.108***	0.0185***	0.00406	-0.0405***
	(0.00795)	(0.00649)	(0.00621)	(0.00627)	(0.00626)
Constant	-0.0450***	-0.00604***	0.00872***	0.0140***	0.0298***
	(0.00148)	(0.00153)	(0.00158)	(0.00157)	(0.00168)
Observations	390,934	390,235	389,535	388,835	388,135

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 30: **Regression Results using Lagged Abnormal Liquidity, the Mean Approach Company Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with company name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImean	0.294***	0.104***	0.0432***	-0.0120***	-0.00915**
	(0.00416)	(0.00358)	(0.00352)	(0.00353)	(0.00367)
ASVImeanEurope	0.193***	0.108***	0.0180***	0.00367	-0.0412***
	(0.00795)	(0.00651)	(0.00623)	(0.00630)	(0.00629)
Constant	-0.0506***	-0.0119***	0.00242	0.00777***	0.0235***
	(0.00140)	(0.00145)	(0.00150)	(0.00149)	(0.00160)
Observations	390,934	390,235	389,535	388,835	388,135

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 31: **Regression Results using Lagged Abnormal Liquidity, the Mean Approach, Company Names and Fixed**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal liquidity and the Abnormal Search Volume Index for the data sample with company name searches. lag.ALN is the lagged abnormal liquidity, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AL1	(2) lag_AL2	(3) lag_AL3	(4) lag_AL4	(5) lag_AL5
ASVImedian	0.290***	0.0920***	0.0298***	-0.0255***	-0.0219***
	(0.00417)	(0.00360)	(0.00355)	(0.00358)	(0.00371)
ASVImedianEurope	0.192***	0.0966***	0.00634	-0.00828	-0.0461***
	(0.00791)	(0.00652)	(0.00627)	(0.00635)	(0.00639)
Constant	-0.0552***	-0.0138***	0.00173	0.00792***	0.0239***
	(0.00140)	(0.00145)	(0.00150)	(0.00149)	(0.00160)
Observations	390,494	389,795	389,095	388,395	387,695

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 32: **Regression Results using Lagged Abnormal Volatility, the Median Approach, Ticker Names and Fixed**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImedian is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

9.3 Volatility

Ticker

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImean	0.00286***	0.00185***	-0.000146	-0.00184***	-0.00271***
	(0.000277)	(0.000272)	(0.000259)	(0.000273)	(0.000282)
ASVImeanEurope	-0.00127***	-0.00194***	-4.41e-05	0.00112***	0.00202***
	(0.000408)	(0.000405)	(0.000410)	(0.000410)	(0.000408)
Constant	0.000599***	0.00269***	0.00419***	0.00532***	0.00560***
	(0.000127)	(0.000124)	(0.000117)	(0.000116)	(0.000116)
Observations	387,399	386,710	386,021	385,332	384,643

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 33: **Regression Results using Lagged Abnormal Volatility, the Mean Approach Ticker Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImean	0.00287***	0.00186***	-0.000156	-0.00186***	-0.00274***
	(0.000280)	(0.000275)	(0.000261)	(0.000274)	(0.000283)
ASVImeanEurope	-0.00128***	-0.00195***	-4.00e-05	0.00114***	0.00205***
	(0.000411)	(0.000408)	(0.000411)	(0.000412)	(0.000410)
Constant	0.000610***	0.00270***	0.00421***	0.00534***	0.00563***
	(0.000125)	(0.000122)	(0.000115)	(0.000114)	(0.000115)
Observations	387,399	386,710	386,021	385,332	384,643

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 34: **Regression Results using Lagged Abnormal Volatility, the Mean Approach Ticker Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImedian	0.00202***	0.00105***	-0.000798***	-0.00232***	-0.00286***
	(0.000284)	(0.000280)	(0.000270)	(0.000286)	(0.000292)
ASVImedianEurope	-0.000482	-0.00137***	0.000347	0.00147***	0.00213***
	(0.000421)	(0.000417)	(0.000413)	(0.000424)	(0.000427)
Constant	0.000589***	0.00270***	0.00423***	0.00536***	0.00566***
	(0.000125)	(0.000122)	(0.000115)	(0.000114)	(0.000115)
Observations	387,130	386,441	385,752	385,063	384,374

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 35: **Regression Results using Lagged Abnormal Volatility, the Median Approach Ticker Names and Fixed Effects**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with ticker name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.

Name

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImean	0.00289***	0.00223***	0.000708***	0.000131	-0.000971***
	(0.000252)	(0.000245)	(0.000234)	(0.000282)	(0.000253)
ASVImeanEurope	0.00142***	-0.000765**	-0.000675*	-0.00143***	-0.000933**
	(0.000388)	(0.000371)	(0.000357)	(0.000394)	(0.000365)
Constant	0.000645***	0.00270***	0.00416***	0.00526***	0.00553***
	(0.000127)	(0.000125)	(0.000118)	(0.000117)	(0.000118)
Observations	383,995	383,306	382,617	381,928	381,240

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 36: **Regression Results using Lagged Abnormal Volatility, the Mean Approach, Company Names and OLS**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with company name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImean	0.00295***	0.00228***	0.000749***	0.000155	-0.000968***
	(0.000255)	(0.000248)	(0.000238)	(0.000287)	(0.000257)
ASVImeanEurope	0.00140***	-0.000807**	-0.000724**	-0.00145***	-0.000962***
	(0.000390)	(0.000373)	(0.000359)	(0.000399)	(0.000369)
Constant	0.000664***	0.00271***	0.00417***	0.00527***	0.00555***
	(0.000124)	(0.000122)	(0.000115)	(0.000115)	(0.000115)
Observations	383,995	383,306	382,617	381,928	381,240

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 37: **Regression Results using Lagged Abnormal Volatility, the Mean Approach, CompanyNames and Fixed Effects**

The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with company name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using mean values to calculate the expected values. ASVImeanEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImean.

VARIABLES	(1) lag_AV1	(2) lag_AV2	(3) lag_AV3	(4) lag_AV4	(5) lag_AV5
ASVImedian	0.00273***	0.00206***	0.000445*	-0.000200	-0.00132***
	(0.000249)	(0.000248)	(0.000257)	(0.000300)	(0.000264)
ASVImedianEurope	0.00121***	-0.00112***	-0.000948**	-0.00136***	-0.000758**
	(0.000410)	(0.000389)	(0.000386)	(0.000421)	(0.000385)
Constant	0.000622***	0.00269***	0.00417***	0.00527***	0.00557***
	(0.000124)	(0.000122)	(0.000116)	(0.000115)	(0.000116)
Observations	383,547	382,858	382,169	381,480	380,792

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 38: **Regression Results using Lagged Abnormal Volatility, the Median Approach, Company Names and Fixed Effects**
The table presents the beta coefficients of the regression studying the relation between lagged abnormal volatility and the Abnormal Search Volume Index for the data sample with company name searches. lag.AVN is the lagged abnormal volatility, with N weeks lag. ASVImean is the Abnormal Search Volume Index using median values to calculate the expected values. ASVImedianEurope are interaction terms, multiplying a dummy variable for Europe with the values of ASVImedian.