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PREDICTING ABNORMAL STOCK MARKET RETURNS AND TRADING VOLUMES USING GOOGLE SEARCH

Henrik Berglin* & Karin Möllborg**

ABSTRACT: We test if investor attention, measured by online search volume in Google, can predict abnormal stock market returns and trading volumes. Specifically, we use online searches for ticker symbols and company names as a proxy for investor attention and hypothesize that an increase in investor attention leads to higher trading volumes and returns in the subsequent weeks. We examine all stocks in the S&P 500 and S&P Europe 350 indices during the period 2005-2014 and control our results for market risk, size, value and momentum factors in accordance with the Carhart (1997) four-factor model. Over a ten-year period, we find that search volume in Google can predict abnormal trading volumes of up to 20% for the following week and yearly abnormal returns of up to 12%. However, when adding trading costs and taxes, the observed abnormal returns will diminish and probably be eliminated in most cases. In addition, we find that the abnormal trading volumes and abnormal returns are considerably higher during the global financial crisis and almost non-existent in the post-crisis period, indicating that the observed abnormal returns are only apparent during exceptional market conditions. Our study contributes to the existing literature on investor attention by reinforcing the relevance of online searches and by providing new insights relating to bull and bear markets, geographical differences and alternative online search measures, that give reason to further scrutinize previous and forthcoming studies relating to investor attention and online search.

TUTOR: Florian Eugster

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* 40662@student.hhs.se
** 50126@student.hhs.se

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1. INTRODUCTION

In this study we show that investor attention can help predict abnormal trading volumes and stock market returns, but that large differences between bull and bear markets as well as geographies exist, which makes it difficult and unreliable for investors to exploit. Traditionally, investor attention is measured by indirect proxies such as media coverage, advertising expenses, abnormal trading volume and analyst coverage. Instead, we employ a more direct measurement by using online searches in Google for company names and ticker symbols as a proxy for investor attention related to a particular stock. Google publicly share information about search volume for all queries typed into its search engine, which enables anyone to discover what people are paying attention to online. By analyzing historical trends of online searches in Google, researchers have been able to predict a variety of things ranging from flu outbreaks (Ginsberg et al., 2009) to unemployment rates (Choi & Varian, 2012). Whether or not it is possible to predict future events and abnormal stock measures in the financial markets is a frequently debated topic in academic literature. We aim to further contribute to this debate by testing if investor attention, measured by online search volume in Google, can predict both abnormal trading volume and abnormal returns.

There are several reasons why we believe online searches in Google is a good measure of investor attention in financial markets. First, online searches is a more direct measure of attention compared to traditional measures such as media coverage, since investors are actively paying attention to what they search for. Second, since Google is the most popular search engine by far in the markets we examine (88% of global market share), we consider the searches made in Google to be a good proxy for all searches made online. Third, previous research shows that there is a strong correlation between investor attention measured by online searches and trading orders by retail investors (e.g. Da et al., 2011).

We examine investor attention by comparing changes in search volume between stocks, rather than comparing absolute levels, by constructing a measure for abnormal search volume which is comparable between firms regardless of size, number of investors, etc. We address the evident possibility that people search for firms for other reasons than trading by employing two different measures of investor attention, namely (1) company names, and (2) ticker symbols, of which we believe the latter captures searches only related to financial information. What we examine in this study is investor attention without any emphasis on sentiment, i.e. if searches have a positive or negative sentiment, since we believe it is difficult to categorize what constitutes positive and negative information (e.g. if a firm fires its CEO or if a company pays too little tax, this could be interpreted as both positive and negative).

Previous research links investor recognition to stock market pricing and liquidity (Merton, 1987) and shows that increased investor attention, measured by e.g. news headlines, leads to abnormally high trading volumes and temporary higher stock prices (Barber & Odean, 2008). Da et al. (2011) show that investor attention, measured by online search volume for stock ticker symbols in Google, has a strong correlation with trading volume, and that an abnormal increase in search volume predicts higher stock prices in the next two weeks. Additional recent studies use online search volume as a measure of investor attention and show that it can help predict trading volume, returns and liquidity (e.g. Joseph et al., 2011).

However, while a number of studies show that online searches can be a good measure of investor attention, there is currently no consensus in academia whether or not investor attention can predict abnormal returns and trading volumes in financial markets. The methodological differences in previous research make it difficult to draw any generalizable conclusions and previous studies provide limited empirical support as the vast majority are confined to a country-specific market, a short period of time and a single set of proxies for investor attention. In particular, most studies have focused on the U.S. market during the years 2004-2008 (e.g. Da et al., 2011; Joseph et al., 2011), a period when the financial markets largely were characterized by the global financial crisis potentially affecting the efficiency of the stock markets (e.g. Lim et al., 2008). In addition, online search data through Google Trends was not made publicly available until May 2006, thus only investors with private access to this information would have been able to earn abnormal returns before that. This gives us reason to question previous findings as they appear both unsustainable and practically unfeasible for investors to exploit.

Thus, we aim to test if previous findings relating to investor attention, trading volumes and abnormal returns hold when covering several markets over a longer period of time not characterized by the financial crisis and when online search data was in fact public. In line with the findings of Barber & Odean (2008) and Da et al. (2011), we therefore hypothesize that an increase in investor attention leads to higher trading volume and returns in the short term. Specifically, we focus on the following three research questions:

Research question 1: Can online search volume for company names and ticker symbols predict abnormal trading volumes?

Research question 2: Can online search volume for company names and ticker symbols predict positive abnormal stock market returns?

Research question 3: Does the predictive power of online search volume for abnormal trading volumes and returns differ between bull and bear markets?

We examine all stocks in the S&P 500 and S&P Europe 350 indices and download weekly search data for the years 2005-2014, resulting in a total of 1,189,536 firm-week observations. To answer our research questions we form portfolios sorted by changes in investor attention, in order to compare trading volume and returns between portfolios with high and low abnormal search volume. In order to control the portfolio returns for outperformance tendency we run regressions using the capital asset pricing model (CAPM), the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model to derive abnormal returns adjusted for market risk, size, value and momentum factors. Over a ten-year period, we find that search volume in Google can predict abnormal trading volumes of up to 20% in the following week and yearly abnormal returns of up to 12%. However, when adding trading costs and taxes, the observed abnormal returns will diminish and probably be eliminated in most cases. In addition, we find that the abnormal trading volumes and abnormal returns are considerably higher during the global financial crisis and almost non-existent in recent bull markets, indicating that the observed abnormal returns are only apparent during exceptional market conditions.

The remaining part of our paper is structured as follows. In Section 2 we present previous research related to investor attention and online search. Section 3 describes our data collection and methodology. Section 4 presents our main results for each research question: (i) abnormal trading volume, (ii) abnormal stock returns, and (iii) how abnormal trading volume and returns varies between bull and bear markets. In section 5 we discuss our results in relation to previous research, acknowledge our study's limitations and make suggestions for future research. In section 6 we summarize our conclusions and highlight the broader implications of our study.

2. PREVIOUS RESEARCH

Information asymmetry and costs make perfect capital markets untenable

Traditional finance theories, such as the capital asset pricing model (CAPM) and the efficient market hypothesis (EMH), assume that market participants are rational and not affected by emotions when making economic decisions. The definition of an efficient market is a market in which prices always fully reflect all available information. In the efficient market hypothesis, Fama (1970) distinguishes between three forms of market efficiency. First, the "weak form" asserts that all price information is fully reflected in asset prices and that current price changes cannot be predicted from past prices. Second, the "semi-strong form" requires asset price changes to fully reflect all publicly available information and not only past prices. Third, the "strong form" postulates that prices fully reflect information even if some investor or group of investors has private access to some information (Fama, 1970). However, in the real world people frequently act irrational, which leads to stock market anomalies that cannot be explained by traditional finance theories. Contradicting evidence to the efficient market hypothesis tries to explain these stock market anomalies through information structures and characteristics of market participants that lead to irrational investment decisions. Kahneman (1973) argues that in the real world, investors do not always have access to all information available on the market, since attention is a scarce cognitive resource and investors need to be selective in information processing. Investors therefore tend to choose stocks for their portfolio based on personal criteria limiting their investment opportunities. Grossman & Stiglitz (1980) argue that when introducing information asymmetry and costs of information, the theories of perfect capital markets become untenable. Since information is costly, prices cannot fully reflect all information available, because then the investors obtaining the information would get no compensation for it (Grossman & Stiglitz, 1980). Returns can therefore be considered to compensate investors for expenses associated with gathering and processing information, and when accounting properly for these expenses the returns are no longer abnormal. Increases in the cost of information thus decrease the number of informed investors, which results in less efficient markets. Conversely, when information is very inexpensive, traders will have more information which leads to more informative prices and efficient markets. Merton (1987) show that in a market with incomplete information, stocks with low investor attention provide higher returns in order to compensate investors for the idiosyncratic risk that cannot be diversified. Idiosyncratic risk is risk associated to a specific asset or small group of assets that has little or no correlation with market risk. It is common to assume in the weak form of the efficient market hypothesis that investors have complete access to the prior history of all stock returns. But for actual decisions, all historical data may not have been in an accessible form or the technology necessary to analyze this data may not yet have been invented.

Some investors trade on information, while others sometimes trade on noise as if it was information. Black (1986) defines the concept of noise traders as non-rational market participants acting based on their beliefs or sentiments not fully justified by fundamental information. The reason for this behavior could be that the noise traders think that the noise they are trading on is information. In most cases, Black (1986) find that noise traders will lose money by trading, while information traders will earn money. Thus, noise makes markets somewhat inefficient, but also prevents market participants from taking advantage of inefficiencies. Furthermore, due to the difficulties of defining noise, there is an ambiguity regarding which investors that are noise traders and which are information traders. While noise traders put noise into stock prices this will be offset by investors trading on information, and the further away a stock price is from its value, the more aggressive information traders will be. Thus, stock prices driven by noise traders tend to revert back towards its value over time (Black, 1986).

Increased investor attention leads to higher trading volumes and a temporary price pressure

Barber & Odean (2008) use news, unusual trading volume and extreme returns as indirect measures of investor attention and examine these against actual trading data from individual and institutional investors. Empirical evidence show that individual investors are more likely to buy attention-grabbing stocks than to sell them, while institutional investors are less inclined to participate in this attention-driven trading. Attention-driven buying is driven by the difficulty individual investors experience when choosing between the thousands of stocks available to buy, while they can sell stocks they already own. Therefore, attention towards a stock increases the numbers of potential buyers but not potential sellers, resulting in a price pressure with a temporary increase in stock price with a subsequent price reversal. Barber et al. (2009) show that not only institutional investors, but also retail investors, can move stock prices and that imbalance in retail trades can forecast future returns. Trading by not fully rational investors can push stock prices away from their fundamental values and when uninformed investors actively buy, assets become temporarily overpriced before eventually reverting to fundamental values. Thus, the results of Barber et al. (2009) are consistent with the theory of noise trading (Black, 1986), in which traders heavily buying can push stock prices away from their fundamental values, making them overvalued, before a subsequent price reversal follows.

Fang & Peress (2009) support the investor recognition theory by Merton (1987) and show that stocks not covered in media earn significantly higher future returns than stocks heavily covered, even when controlling for market, size, book-to-market, momentum and liquidity factors. The difference is most substantial for small stocks, stocks with low analyst following, stocks with many retail investors and stocks with high idiosyncratic volatility. Therefore, idiosyncratic risk can be eliminated from a portfolio by using adequate diversification. Thus, in informational incomplete markets, stocks with lower investor recognition need to generate higher returns as a compensation for imperfect diversification (Fang & Peress, 2009).

Online search volume as a proxy for investor attention

Traditionally, a variety of indirect proxies for investor attention are used, such as advertising expenses (Lou 2013), media coverage (Fang & Peress 2009), abnormal trading volume (Hou et al. 2008), extreme returns and news headlines (Barber & Odean 2008). Using these indirect measurements of investor attention implies several difficulties in measuring the actual effect. These measurements rely on the critical assumption that if a company name was mentioned in news media, it is assumed that the investors have paid attention to it, which is not always the case (Da. et. al 2011).

Da. et al. (2011) propose a new and direct measurement of investor attention through the aggregate online search frequency in Google, called Search Volume Index (SVI). SVI is publicly available data via the online tool Google Trends[1]. Da et al. (2011) are using weekly SVI, which is the number of searches for a specific search term scaled by its time-series average. This data is provided for all different types of topics, and not only companies. For example the SVI for “diet” declines during Christmas and peaks in January, indicating that individuals pay less attention to dieting during the holidays but more attention in the beginning of the year as

[1] http://www.google.com/trends

part of a New Year's resolution (Da et al., 2011).

Google search index can be considered as a good way of measuring investor attention for a number of reasons. First, Internet users commonly use a search engine to collect information and Google has a dominant market position (88 %) around the world. Thus, the search volume by Google is likely to be representative for the Internet search behavior of the general population. Second, and more importantly, search is an active attention measurement and if the investor is searching for a stock, the investor is paying attention to it. Third, by comparing SVI for company tickers and retail order execution from SEC Rule 11Ac1-5 (Dash-5) reports, Da et al. (2011) find a strong and direct correlation between SVI changes and trading by retail investors.

Da et al. (2011) confirm the attention-induced price pressure hypothesis of Barber and Odean (2008) and find that search volume is a direct way to reveal and quantify the interests of investors. By searching for ticker symbols of stocks in a sample of the Russell 3000 index on Google Trends, Da et al. (2011) find that an abnormal increase in SVI predicts higher stock prices in the next two weeks and a price reversal within the year. In addition, SVI is also found to predict large first-day returns and long-run underperformance for a sample of IPO stocks.

A number of recent studies test the theories of Da et al. (2011) and Barber and Odean (2008) using samples from different markets in order to predict trading volume, returns and liquidity. The results of these studies vary depending on markets, control variables and methods applied. Joseph et al. (2011) find that online ticker searches serve as a valid proxy for investor sentiment and that search intensity can predict abnormal stock returns and trading volumes over a weekly horizon for the U.S. market over the period 2005–2008. Bank et al. (2011) use company name as search measure and find that SVI captures the attention of uninformed investors, resulting in reduced information asymmetry, improved liquidity and a short-term buying pressure on the German Stock market. Amin and Ahmad (2013) find that investor attention partially affects profitability, liquidity and volatility, by examining a sample of 42 firms listed on the Karachi Stock Exchange. Vozlyublennaia (2013) finds that attention can alter predictability of index returns and argue that increased investor attention diminishes return predictability and, therefore, improves market efficiency. Takeda and Wakao (2014) find a strong correlation between trading volume and search intensity, by using a sample consisting of 189 companies listed on the Japanese stock exchange during the period 2008-2011, and argue that individual investors search more actively for information for companies that they already own in financial crises. Fang et al. (2014) use searches on Baidu and find that individual investors' attention and market return have joint positive effects on short-term stock returns on the ChiNext stock market.

Further elaboration on previous research

Previous research within investor attention provides several interesting findings; Merton (1987) links investor attention to stock market pricing and liquidity, Barber & Odean (2008) show that investor attention can be used to predict stock market prices, Da et al. (2011) show that online search volume in Google is correlated with trading volume and stock prices in the short term, and Joseph et al. (2011) show that online searches can help predict trading volume, returns and liquidity. Furthermore, academics provide several alternative explanations of investor attention and its implications; while some argue that increased investor attention implies more informed investors and thus more efficient markets (Aouadi et al., 2013), others argue that it puts additional noise into prices that make markets less efficient (e.g. Da et al., 2011). However, although a number of studies show that online searches can be a good measure of investor attention and offer valuable suggestions for investors to consider, there is currently no consensus in academia whether or not investor attention can predict abnormal returns and trading volumes in financial markets. The methodological differences in previous research make it difficult to draw any generalizable conclusions and previous studies provide limited empirical support as the vast majority are confined to a country-specific market, a short period of time and a single set of proxies for investor attention.

In particular, most studies relating to investor attention and online search have focused on the U.S. market during the years 2004-2008 (e.g. Da et al., 2011; Joseph et al., 2011), a period when the financial markets largely were characterized by the global financial crisis (2007-2009). However, previous research show that financial crises adversely affect the efficiency of stock markets (e.g. Lim et al., 2008) and more recent studies relating to investor attention show that trading strategies based on online searches can be highly profitable especially during the financial crisis (e.g. Gwilym et al., 2014). In addition, online search data through Google Trends was not made publicly available until May 2006, thus making it impossible for investors to access the information before that, which means that it was not incorporated into stock prices according to the semi-strong form of the efficient market hypothesis. Thus, only investors with private access to this information would have been able to earn abnormal returns before it was released publicly. While several of the central studies in the field claim that it is possible to predict returns and trading volumes with online search data, the fact that they are based on a period partly of which the information was not public and partly affected by the financial crisis, there is reason to believe that their findings are both unsustainable and practically unfeasible for investors to exploit.

Thus, considering the inconclusive findings and lack of consistency in methodologies in previous literature, investors could benefit from a more comprehensive and uniform study covering several markets over a longer period of time - not characterized by the financial crisis and when online search data from Google Trends was in fact public - in order to better know how investor attention and online searches can be useful in the financial markets.

3. DATA COLLECTION AND METHOD

3.1 Data collection

While most previous studies focus on a single market, we include both the U.S. and the European market in order to be able to draw more generalizable conclusions. Including the U.S. market also makes our study more comparable to previous studies such as Da et al. (2011) and Joseph et al. (2011). To test our hypotheses we use the S&P 500 and S&P Europe 350 indices representing the U.S. and the European market. Both S&P 500 and S&P Europe 350 are float-adjusted, market-capitalization-weighted indices that include the largest and most- liquid stocks from the U.S. and Europe. The S&P 500 index is the largest American stock market index, based on market capitalizations of the 500 largest companies that have common stocks listed on the NYSE or NASDAQ. The S&P 350 Europe index covers 83.3 % of S&P Europe broad market indices, which represents approximately 99% of the float-adjusted market capitalization within each country included in the index.

Our sample period ranges from January 1, 2005 to December 31, 2014. Thus, our study covers a longer time period than previous studies within investor attention and online search, which enables us to further analyze historical trends as well as compare different time periods and market states. In order to eliminate survivorship bias and the impact of index additions and deletions, we examine all 714 stocks included in the S&P 500 index and

Table 1: CHARACTERISTICS OF STOCK MARKET INDICES

	S&P 500	S&P Europe 350
Number of Constituents	502	350
Historical additions (2005-2014)	212	94
Total Number of Constituents (2005-2014)	714	444
	[USD millions]	[EUR millions]
Max Market Cap	728,967	248,941
Min Market Cap	3,692	1,340
Mean Market Cap	38,937	26,322
Median Market Cap	18,682	14,150
Sector breakdown	Information Technology 19.9% Information Technology 19.9% Financials 16.1% Health Care 14.6% Consumer Discretionary 12.5% Industrials 10.3% Consumer Staples 9.5% Energy 8.5% Materials 3.2% Utilities 3% Telecommunication Services 2.3%	Financials 22% Health Care 14.4% Consumer Staples 13.5% Consumer Discretionary 11.3% Industrials 10.9% Energy 7.9% Materials 7.6% Telecommunication Services 4.7% Utilities 4.1% Information Technology 3.5%

In Table 1 we show descriptive information of the S&P 500 index and the S&P Europe 350 index. The table shows, from top to bottom, number of current constituents in each index, additions of stocks included in the index anytime during 2005-2014, total number of constituents per index, the highest market cap for a stock in the index, the lowest market cap for a stock in the index, the mean market cap, the median market cap and the a breakdown of sectors represented in each index. Market capitalization and sector breakdown values in the table are as of April 30, 2015.

all 444 stocks included in S&P Europe 350 index anytime during the ten-year sampling period.

3.1.1 Online search volume

As a direct proxy for investor attention we use online search volume in Google for each stock in our sample. We consider searches in Google to be a good proxy for the total amount of online searches made in the U.S. and in Europe since it is the most popular search engine in both markets and currently represents 88% of the global search engine market. Through a publicly available tool called Google Trends (www.google.com/trends), Google publishes a daily, weekly and monthly index measuring the popularity of all search queries typed into its online search engine. Daily search volume index (SVI) is available for the last three months, while weekly and monthly SVI is available since January 1, 2004. In our study we use weekly SVI as this is consistent with our research focus, but exclude the year 2004 from our sample due to very volatile SVI data in line with Da et al. (2011).

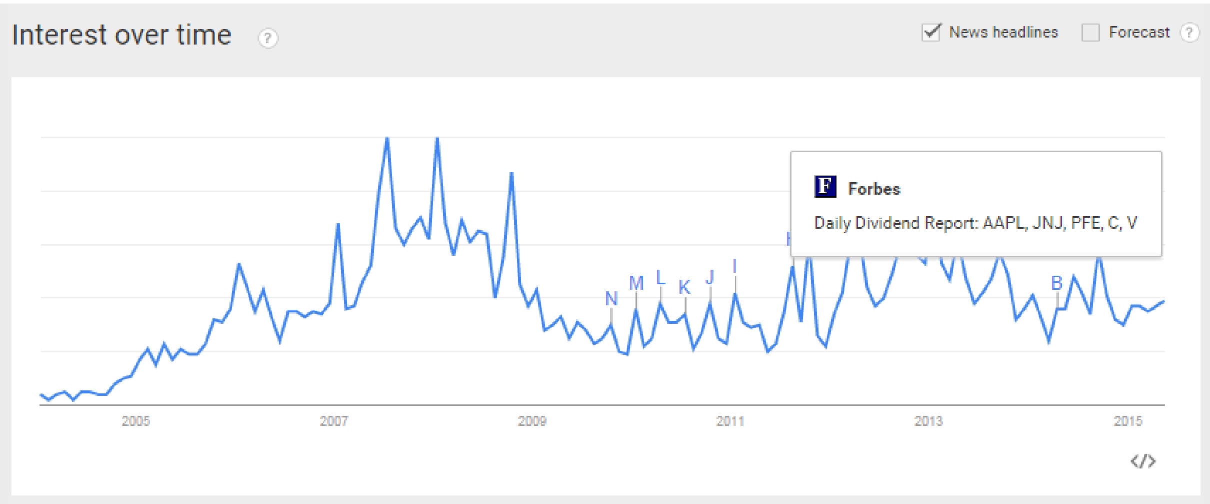
Google Trends does not provide data for specific search queries in absolute numbers, but instead the SVI is constructed such that a value of 100 is assigned to the point in time when a search query had the largest search volume relative to the total number of searches on Google for the specified time period. All SVI values are in the range of 0-100, where 100 implies highest possible SVI and 0 in a period means that the search volume does not meet a designated threshold. Our SVI data is also scaled appropriately to temporal variations in overall search intensity, meaning that the SVI for each firm is relative to the total number of searches on Google to account for e.g. holidays when the total number of searches is lower. The construction of SVI restricts our study to analyze the changes in search volume between stocks, rather than absolute levels of investor attention. However, as SVI values are relative both to the overall number of searches in Google and the peak for each specific search query, we can see differences in relative investor attention for each stock in our sample which enables us to sort all stocks based on changes in investor attention.

In order to identify searches for stocks in Google there are three main problems addressed in previous research. First, investors might search for a company name without any intention to invest, for instance by searching the query "Apple" in order to buy a phone rather than having the intention to trade Apple stocks. Second, stocks might have ambiguous company names with multiple meanings, e.g. it can be hard to know if someone searches for the fruit or the company "Apple". Third, investors might use different variations of the same company names as search queries, e.g. "Apple", "Apple Inc", "Apple stock" or "APPL".

We address all three issues by employing two different methods to assess SVI. First, we use a common approach of measuring search volume for ticker symbols to ensure searches are related to investing. As argued in previous studies (e.g. Da et al., 2011; Joseph et al., 2011), ticker symbols captures only searches from people interested in investing in the company and is less ambiguous than company names. Ticker symbols are also uniquely assigned and thus eliminate the problem of multiple reference names.

Second, we use a novel approach where we measure "topic search" for each company in which multiple variations of the company name are included while simultaneously filtering out unrelated searches if the name has ambiguous meaning. The "topic search" function uses Google's algorithms to derive what search terms that are actually related to the specific company. For instance, when using topic search for "Tokyo - Capital of Japan", Google Trends aggregates many different search queries that relate to the same topic,

Figure 1: ILLUSTRATION OF SEARCH VOLUME INDEX (SVI) IN GOOGLE TRENDS



In figure 1 we show an illustration of the search volume index (SVI) in Google Trends for the ticker symbol "AAPL" used to identify stocks of Apple Inc. listed on NASDAQ. The search volume index (SVI) provided by Google Trends is publicly available at www.google.com/trends. SVI is constructed such that a value of 100 is assigned to the point in time when a search query had the largest search volume relative to the total number of searches on Google for the specified time period. Google Trends also provides information related to each specific search query, such as regional information, related search queries and news headlines linked to peaks and drops in SVI (e.g. in Figure 1 we see that a news article mentioning dividends for AAPL is linked to a certain peak in SVI).

Table 2: DESCRIPTIVE STATISTICS OF OUR SAMPLE BY INDEX AND SVI METHOD

	S&P 500		S&P Europe 350		Total
Current stocks	502		350		852
Historical additions	212		94		308
Total stocks	714		444		1,158
SVI method	Company names	Ticker symbols	Company names	Ticker symbols	Total
Firm-week observations	366,996	366,996	227,772	227,772	1,189,536
Missing observations	103,609	279,039	168,460	168,973	720,081
Missing observations (%)	28%	76%	74%	74%	
Valid SVI observations	263,387	87,957	59,312	58,799	471,455

In Table 2 we show descriptive statistics of the data in our different samples. The table show, from top to bottom, the current number of stocks per index, historical additions to each index due to changes in constituents during the sampling period, total number of stocks per index, the number of firm-week data points per index and SVI method, the number of missing observations due to missing search volume in Google Trends or missing stock market data (e.g. when a company is delisted), missing observations in percentage, and total number of observations per index and SVI method.

including variations in different languages (e.g. 東京, Токио, Tokyyo, Tokkyo, Japan Capital). In the same way "topic search" allows us to filter out searches not related to a specific company, e.g. when someone is searching for the fruit apple rather than the company Apple, those searches are not included in the SVI. By employing the "topic search" approach we aim to capture a much larger base of retail investors than collecting SVI data for just ticker symbols. Users may search for a company name to obtain a great variety of information that may not be directly associated with investing decisions but still affect investor attention in a broader sense (e.g. product information, recruitment or general company news) (Takeda & Wakao, 2014). Using SVI for company names through "topic search" we are also more likely to capture individual or retail investors which we aim to do, since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg terminals (Da et al., 2011).

A number of data exclusions are made. Stocks that are not available as company names for topic searches are excluded. In line with Da et al. (2011), all ticker symbols that have too generic symbols, for example "AIR" or "MMM", are excluded. Google Trends also provide certain functions that help us to examine if the searches are related to the specific company that we are interested in, such as in which region the searches are made in and other terms associated with financial information searching, for example "stocks", "dividend" etc. Also stocks that are duplicated in the stock data but only appear once in the SVI data (e.g. the company Volvo only has one set of search data but can be traded as both A and B shares) are excluded to only include one version of the same stock.

To collect SVI data for all stocks in our sample we download SVI for both ticker symbols and company names for all 1,158 stocks included in our sample to get weekly data for the ten-year sampling period. This gives us a total of 366,996 firm-week observations for S&P 500 for each SVI measure and 227,772 observations for S&P Europe 350 for each SVI measure. In total, we are able to collect 1,189,536 firm-week observations and 471,455 valid SVI observations.

3.1.2 Stock market data

We collect stock market data from Thomson Reuters Datastream covering all stocks traded on the S&P 500 and S&P Europe 350 indices during our sample period 2005-2014. Trading volume is defined as number of shares traded for a stock in a particular week. The figures are adjusted for capital events and for stocks traded on more than one exchange in the same country, we use volume from the primary exchange in that country except for U.S. listed shares where we consolidate volume from all exchanges on which the share is listed. For measuring returns, we collect data for a total return index showing a theoretical growth in value of a stock assuming that dividends are re-invested at the closing price on the ex-dividend date. We use gross dividends where available and ignore tax and re-investment costs in the calculations when calculating the total return index.

3.2 Method

3.2.1 Abnormal Search Volume Index (ASVI) and portfolio formation

In line with previous studies using online searches as a proxy for investor attention (e.g. Da et al., 2011), we are interested in what happens to trading volume and stock returns when online search volume deviates from what is expected. In accordance with Da et al. (2011), we create a measure of abnormal search volume index (ASVI), which enables us to compare relative changes in SVI between stocks rather than comparing absolute levels, thus making changes in search volume comparable between stocks despite different market capitalizations, number of investors, etc.

We define abnormal search volume index (ASVI) as:

$$ASVI_t = \log(SVI_t) - \log[\text{median}(SVI_{t-1},\ldots,SVI_{t-8})]$$

where $\log(SVI_t)$ is the common logarithm (with base 10) of the search volume index (SVI) at week t, and $\log[\text{median}(SVI_{t-1},\ldots,SVI_{t-8})]$ is the logarithm of the median SVI during the prior eight weeks. The median of the prior eight weeks represents the expected SVI and is more robust to one-week peaks or drops compared to using the mean. A large positive ASVI represents an increase in investor attention, while a large negative ASVI represents a decrease, making the measure appropriate to compare between all stocks in our sample.

When ASVI is calculated for each stock and week, we sort the stocks into quantiles forming ten portfolios based on ASVI from the prior week, with stocks with the highest ASVI in Q10 and stocks with the lowest ASVI in Q1. The stocks are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI.

3.2.2 Abnormal Trading Volume (ATV)

To answer our first research question, if increased search volume can predict abnormal trading volumes, we also need to construct a measure for abnormal trading volume (ATV). Using the number of shares traded for a stock on a particular day as trading volume, we define abnormal trading volume (ATV) in accordance with Joseph et al. (2011) as:

$$ATV = (TV_{i,t} - TV_{i,avg}) / (TV_{i,avg})$$

where $TV_{i,t}$ is the trading volume for firm i during week t and $TV_{i,avg}$ is the average of the weekly trading volume during all previous weeks in the sampling period. To avoid bias in the beginning we also include the average trading volume of the past eight weeks prior to our sampling period.

We then calculate the abnormal trading volume for each stock and week to get the average ATV per portfolio and week. The portfolios are based on ASVI from the prior week and resorted in the beginning of each week based on new levels of ASVI.

In order to test the statistical significance of abnormal trading volume for each portfolio we perform one sample t-tests to determine if each value differs from zero. We also perform independent samples t-tests to determine if there is a difference between the mean values in abnormal trading volume for the portfolio with highest ASVI (portfolio Q10) and the portfolio with lowest ASVI (portfolio Q1). We then report if our calculated p-values are below our chosen thresholds for statistical significance at the 0.10, 0.05 and 0.01 levels.

3.2.3 Abnormal Returns (AR)

To answer our second research question, if changes in search volume can predict abnormal returns, we also need to construct a measure of abnormal return (AR). We apply three different models including risk factors in order to get the abnormal return measure, namely the capital asset pricing model (CAPM), the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. If ASVI can predict abnormal returns, we expect the alpha to be positive and significant in the portfolio with highest ASVI (Q10) and in the long-short portfolio in which we go long in Q10 and short in Q1. To obtain the abnormal return, we regress the returns from the equally weighted portfolios sorted by abnormal search volume (ASVI) using the risk factors for each asset pricing model. The abnormal return, alpha, is then the portfolio's returns that cannot be explained as a compensation for added risk. In an efficient market, the expected abnormal return (alpha) is zero, thus the alpha coefficient indicates how well a portfolio performs after accounting for risk and is often used to assess the performance of fund managers.

The CAPM model determines the appropriate required rate of return by taking the asset's sensitivity to non-diversifiable risk, the expected market return and the expected risk-free return. Using the CAPM, we obtain the abnormal return per portfolio by performing the following regression:

$$R_{i,t} - R_{f,t} = \alpha + \beta_i (R_{M,t} - R_{f,t}) + \varepsilon_{i,t}$$

where $R_{i,t} - R_{f,t}$ is the portfolio's return in excess of the risk-free return, α (alpha) is the abnormal return, $\beta_i (R_{M,t} - R_{f,t})$ is the non-diversifiable risk including beta (β_i), market return ($R_{M,t}$) and risk-free return ($R_{f,t}$), and $\varepsilon_{i,t}$ is the error term.

The Fama-French (1993) three-factor model is an extension of the capital asset pricing model (CAPM) by adding size and value factors in addition to the market risk factor. The three-factor model takes into account that value and small cap stocks outperform the market on a regular basis. By including these two additional factors, the model adjusts for outperformance tendency and could thus be considered as a better tool for measuring abnormal returns. First, the size factor measures the extra risk in small cap companies compared to large cap companies. In the long run, small cap stock returns tend to exceed returns from large cap stocks and the SMB factor (Small Minus Big market capitalization) is supposed to compensate for the increased risk associated with this additional return. Second, value stocks are companies that tend to have lower earnings growth rates, higher dividends and lower prices compared to their book value than growth stocks, which is compensated for by the HML (High Minus Low book-to-market ratio) factor. In the long run, value stocks have generated higher returns than growth stocks because of the higher risk.

Using the Fama-French three-factor model, we obtain the abnormal return per portfolio by performing the following regression:

$$R_{i,t} - R_{f,t} = \alpha + \beta_i (R_{M,t} - R_{f,t}) + \beta_{SMB}(SMB_t) + \beta_{HML}(HML_t) + \varepsilon_{i,t}$$

where $R_{i,t} - R_{f,t}$ is the portfolio's return in excess of the risk-free return, α (alpha) is the abnormal return, $\beta_i (R_{M,t} - R_{f,t})$ is the non-diversifiable risk, SMB_t is the premium of the size factor (Small Minus Big market capitalization), HML_t is the premium of the book-to-market factor (High Minus Low book-to-market ratio), and $\varepsilon_{i,t}$ is the error term.

As a further extension of the Fama-French three-factor model, Carhart (1997) added a fourth factor in order to adjust for momentum

Table 3: BULL AND BEAR MARKET CLASSIFICATION

Period	Months	Market state
Jan, 2005- Oct, 2007	34	Bull
Nov, 2007- Feb, 2009	16	Bear
Mar, 2009- Dec, 2014	70	Bull

In Table 3 we show the classification of Bull and Bear market states for the S&P 500 index and the S&P Europe 350 index. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. The first 34 months are classified as bull market (Jan, 2005- Oct, 2007), the following 16 months are classified as bull market (Nov, 2007- Feb, 2009) and the last 70 months are classsified as bull market (Mar, 2009- Dec, 2014).

outperformance. Momentum in a stock is described as the probability for a stock price to continue to rise when it is going up and to continue to decline if it is going down. The momentum factor UMD (Up-Minus-Down) is calculated by subtracting the equally weighted average of the highest performing firms from the equally weighed average of the lowest performing firms, lagged one month (Carhart 1997).

Using the Carhart four-factor model, we obtain the abnormal return per portfolio by performing the following regression:

$$R_{i,t}-R_{f,t} = \alpha + \beta_i(R_{M,t} - R_{f,t}) + \beta_{SMB}(SMB_t) + \beta_{HML}(HML_t) + \beta_{UMD}(UMD_t) + \varepsilon_{i,t}$$

where $R_{i,t}-R_{f,t}$ is the portfolio's return in excess of the risk-free return, α (alpha) is the abnormal return, $\beta_i(R_{M,t} - R_{f,t})$ is the non-diversifiable risk, SMB_t is the premium of the size factor (Small Minus Big market capitalization), HML_t is the premium of the book-to-market factor (High Minus Low book-to-market ratio), UMD_t is the premium of winners-minus-losers (Up-Minus-Down) factor, and $\varepsilon_{i,t}$ is the error term.

We collect the factor data for the Fama-French three-factor model and the Carhart four-factor model from Kenneth French's website[2] for both the U.S. and the European market. Factors for the U.S. market are available on a weekly basis, whereas factors for the European market are only available on a monthly basis. Thus, in order to make the European data usable, we compound our weekly portfolio returns into monthly data. We then regress the returns from the equally weighted portfolios sorted by abnormal search volume (ASVI) using the risk factors in the Carhart four-factor model to obtain abnormal returns.

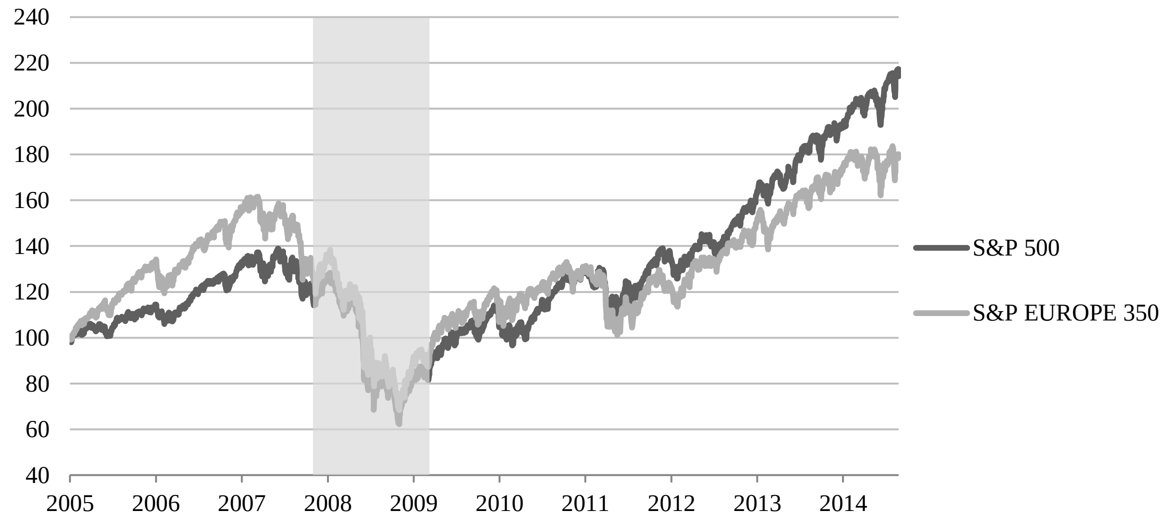
As we hypothesize that ASVI can predict abnormal returns, we expect a positive significant alpha ($\propto$) for the both the portfolio with highest ASVI (Q10) and the long-short portfolio (Q10-Q1). Since we are only interested in testing if there is a positive abnormal return, we use a one-tailed test to determine the statistical significance of the alpha coefficient. A positive alpha for the long-short portfolio would mean that investing in the portfolio with highest ASVI (Q10) and short-selling the portfolio with lowest ASVI (Q1) would generate an abnormal return attributable to differences in ASVI. The coefficient for the market risk factor (Mkt- Rf) is expected to be close to 1 for all 10 portfolios. A coefficient of 1 implies that when the market return increases by 1 %, our portfolio also increase by 1 %. For large cap samples, such as the S&P 500 and S&P Europe 350, the coefficients for size (SMB) and book-to-market (HML) are expected to be less significant compared to a sample with different sizes of stocks (small-, mid- and large cap).

3.2.4 Bull and bear markets

Bull and bear markets can be defined in various ways, but simply refers to long-term upward (bull) and downward (bear) trends in stock prices. In line with Pagan and Sossounov

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html

Figure 2: BULL AND BEAR MARKET CLASSIFICATION



In Figure 2 we show the classification of Bull and Bear market states for the S&P 500 index and the S&P Europe 350 index. We define a bull (bear) market as a positive (negative) change greater than 20% in stock price index that lasts for at least three months. The first 34 months are classified as bull market (Jan, 2005- Oct, 2007), the following 16 months are classified as bull market (Nov, 2007- Feb, 2009) and the last 70 months are classsified as bull market (Mar, 2009- Dec, 2014). The bear market (Nov, 2007- Feb, 2009) is highlighted in grey.

(2003), we define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. Using this methodology we split our sample into three sub-periods by different market states as we show in Figure 2, resulting in the same periods for both markets. The three sub-periods we get are as follows: the first period is a bull market from January 2004 to October 2007, the second period is a bear market lasting from November 2007 until February 2009 (the global financial crisis) and the third period is a bull market period from Mars 2009 to December 2014 when our sample period ends.

3.2.5. Model assumptions

To ensure our model is not affected by multicollinearity we perform a correlation analysis of the independent variables. As we show in Table 4, two correlation coefficients are over 0.5, which indicates that our model could be affected by multicollinearity. To test this, we calculate Variance Inflation Factor (VIF) values for each independent variable in the regressions. We find that all independent variables in our regressions have VIF values under 2 and thus we conclude that our model is not affected by multicollinearity. In order to correct for potential autocorrelation and heteroscedasticity in the error terms in our

Table 4: CORRELATION OF INDEPENDENT VARIABLES

	U.S.					Europe			
	Mkt-RF	*SMB*	*HML*	*UMD*		*Mkt-RF*	*SMB*	*HML*	*UMD*
Mkt-RF	1				*Mkt-RF*	1			
SMB	0.265493	1			*SMB*	-0.00421	1		
HML	0.444103	-0.02489	1		*HML*	0.584758	-0.07425	1	
UMD	-0.39831	0.029262	-0.5669	1	*UMD*	-0.42486	-0.01664	-0.4836	1

In Table 4 we show correlations between the independent variables in our regression analysis split by market. The table shows, from top to bottom, market, risk factors in the Carhart four-factor model, the Market-Risk factor (Mkt-RF), the size factor (SMB), the value factor (HML) and the momentum factor (UMD).

model, we use the Newey-West (1987) variance estimator, which produces consistent standard errors for OLS regression coefficient estimates when there is autocorrelation and heteroscedasticity.

4. FINDINGS

This section presents our empirical findings. First, we show the relation between abnormal search volume (ASVI) and abnormal trading volume (ATV). Second, we show the relation between ASVI and returns, starting with raw returns followed by abnormal returns (AR) that are risk-adjusted using the Carhart four-factor model. Third, we show the relation between ASVI, ATV and AR when controlling for market states. Finally, we discuss the robustness of our findings by testing alternative variations of ASVI, by changing the number of portfolios and by testing different asset pricing models.

4.1 Can online search volume predict abnormal trading volume?

In order to answer our first research question, if abnormal search volume index (ASVI) can predict abnormal trading volume (ATV), we form ten portfolios based on ASVI from the prior week and calculate the mean ATV for each portfolio as we show in Table 5. We can see a clear association between ASVI and ATV, since the mean values for ATV increase when moving from portfolio Q1 towards portfolio Q10 for all samples. We find a significant difference between the means of the portfolios with highest and lowest ASVI, ranging from 4% to 20%, implying that ASVI can predict ATV of up to 20% the following week for the U.S. market (S&P 500) when using ticker symbols as a proxy for investor attention.

In Table 6 we show that the relationship between ASVI and ATV for the long-short portfolio (Q10-Q1) is considerably higher in week zero than the following weeks for all of our four samples. For the U.S. market we find that the difference in ATV between portfolio Q10 and Q1 is gradually decreasing from week zero to week four, i.e. for each week further away from when the ASVI is observed. For the

Table 5: ABNORMAL TRADING VOLUME BY PORTFOLIOS BASED ON ASVI PREVIOUS WEEK

	U.S. Company names	U.S. Ticker symbols	Europe Company names	Europe Ticker symbols
Q1	11.5%***	10.6%***	-9.4%***	-7.4%***
Q2	11.0%***	9.6%***	-8.7%***	2.2%
Q3	11.7%***	9.2%***	-6.2%***	-7.3%***
Q4	11.9%***	9.3%***	-6.2%***	-7.0%***
Q5	12.6%***	10.1%***	-4.8%***	-9.2%***
Q6	12.5%***	10.4%***	-1.7%	-4.7%***
Q7	12.4%***	12.0%***	1.9%	-7.1%***
Q8	12.3%***	12.3%***	-4.1%***	-8.3%***
Q9	13.4%***	17.1%***	-6.2%***	-7.7%***
Q10	24.6%***	30.9%***	0.3%	-3.3%**
Q10 minus Q1	13.1%***	20.2%***	9.7%***	4.1%***

In Table 5 we show the mean trading volume per portfolio. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. The weekly abnormal trading volume (ATV) is computed as $ATV = (TV_{i,t} - TV_{i,avg}) / (TV_{i,avg})$*, where* $TV_{i,t}$ *is the trading volume for firm i during week t and* $TV_{i,avg}$ *is the average of the weekly trading volume during all previous weeks in the sampling period. We then calculate the abnormal trading volume per week to get the average abnormal trading volume per portfolio. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Table 6: WEEKLY DIFFERENCE IN ABNORMAL TRADING VOLUME BETWEEN PORTFOLIO Q10-Q1

	U.S. Company names	U.S. Ticker symbols	Europe Company names	Europe Ticker symbols
Week 0	27.5%***	50.4%***	22.2%***	7.4%***
Week 1	13.1%***	20.2%***	9.7%***	4.1%**
Week 2	7.9%***	11.3%***	0.1%	3.1%**
Week 3	5.3%*	10.3%***	3.8%*	2.1%*
Week 4	4.4%*	5.5%*	3.5%	2.1%*

In Table 6 we show the difference in abnormal trading volume (ATV) between the portfolio with the highest and lowest ASVI (i.e. portfolio Q10 minus Q1) by different time-horizons between ASVI and ATV. Week 0 contains the ATV the same week as we see the ASVI, while Week 4 contains the ATV four weeks after we see the ASVI change and rebalance the portfolios. The weekly abnormal trading volume (ATV) is computed as $ATV = (TV_{i,t} - TV_{i,avg}) / (TV_{i,avg})$, *where* $TV_{i,t}$ *is the trading volume for firm i during week t and* $TV_{i,avg}$ *is the average of the weekly trading volume during all previous weeks in the sampling period. We then calculate the abnormal trading volume per week to get the average abnormal trading volume per portfolio, and compute the difference between portfolio Q10 and Q1 to get the values for each time horizon. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

European samples we see a similar pattern with the highest difference in ATV week zero followed by week one, after which the difference in ATV decreases the subsequent weeks.

4.2 Can online search volume predict abnormal returns?

In order to answer our second research question, if ASVI can predict abnormal returns, we form portfolios based on ASVI and regress the return for each portfolio using the Carhart four-factor model to adjust for outperformance tendency. As we hypothesize that ASVI can predict abnormal returns, we expect the alphas for portfolio Q10 and for the long-short portfolio Q10-Q1 to be positive and significant. As we show in Table 7, for the U.S. market we find significant positive alphas for a long position in portfolio Q10 two weeks after the ASVI is observed, whereas for Europe we only find a positive significant alpha for the second week when using company names as SVI measure. However, the long-short portfolios Q10-Q1 are not significant for any market or SVI measure, which means that a zero-investment strategy in which we take a long position in the portfolio with high ASVI stocks and a short position in the portfolio with low ASVI stocks would not generate any significant abnormal returns. Although

Table 7: ABNORMAL RETURN (ALPHA) PER YEAR BY MARKET AND SVI MEASURE

	U.S. Company names	U.S. Ticker symbols	Europe Company names	Europe Ticker symbols
Q10 (week 1)	5.2%**	10.6%**	6.3%*	8.6%*
Q10 (week 2)	7.9%***	12.3%***	10.1%***	4.90%
Q10 minus Q1 (week 1)	1.90%	3.70%	-2.04%	0.00%
Q10 minus Q1 (week 2)	3.30%	5.80%	0.00%	-1.70%

*In Table 7 we show a summary of yearly abnormal return (alpha) per sample and portfolio, after risk adjusting returns in accordance with the Carhart four-factor model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) and each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. We then measure returns either one or two weeks after we observe the ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Table 8: RETURNS FOR COMPANY NAMES – U.S.

A. Raw returns per week by portfolio based on ASVI for different investment horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5
Q1	0.18%	0.27%	0.30%	0.32%	0.38%	0.36%
Q10	0.46%	0.31%	0.36%	0.26%	0.28%	0.26%
Q10-Q1	0.28%	0.04%	0.06%	-0.06%	-0.11%	-0.10%

B. Abnormal return per week when investing *one* week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0006	1.0994***	0.2490***	0.1269***	-0.1831***	89.91%
	(1.27)	(49.59)	(5.53)	(2.63)	(-7.49)	
Q10	0.0010**	1.1297***	0.1437***	0.2102***	-0.1470***	87.85%
	(1.81)	(45.16)	(2.83)	(3.86)	(-5.33)	
Q10-Q1	0.0004	0.0303	-0.1053*	0.0833	0.0361	1.20%
	(0.57)	(1.02)	(-1.74)	(1.29)	(1.10)	

C. Abnormal return per week when investing *two* weeks after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0008**	1.1275***	0.2394***	0.2173***	-0.1892***	90.57%
	(1.75)	(50.60)	(5.29)	(4.49)	(-7.70)	
Q10	0.0015***	1.1044***	0.1569***	0.2127***	-0.1751***	89.30%
	(2.93)	(47.71)	(3.34)	(4.23)	(-6.86)	
Q10-Q1	0.0006	-0.0231	-0.0826	-0.0046	0.0141	1.02%
	(1.05)	(-0.84)	(-1.48)	(-0.08)	(0.47)	

*In Table 8 we show returns for the U.S. market (S&P 500) when using company names as SVI measure. Table 8A shows weekly raw returns for different time-horizons for changes in search volume and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the stocks with the highest ASVI and Q1 contains the stocks with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we observe the ASVI, while Week 5 contains the raw returns five weeks after we observe the ASVI. In Table 8B and 8C we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model. Table 8B and 8C show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We have sorted the portfolios based on ASVI and invest one or two weeks after the observed ASVI. Number of observations: 512. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

insignificant, we get consistent positive alphas for the U.S. market for the long-short portfolios, while we get negative or no abnormal returns for the long-short portfolios for the European market. Thus, our findings show that a long position in Q10 generate both higher and more significant alphas than a long-short position. In the following section, we show our findings related to ASVI and returns in more detail by market and SVI measure.

In Table 8A we show the difference in raw returns between the portfolio including stocks with high ASVI (Q10) and low ASVI (Q1) for the U.S. market when using company names as SVI measure. We find that the highest weekly raw return (0.28%) for the long-short portfolio (Q10-Q1) is observed in week zero, i.e. the same week as we observe the ASVI, followed by a positive raw return in week one and week two. Thereafter, we find a price reversal starting in week three, where the raw return for our long-short portfolio changes from positive to a negative weekly return of -0.06% and thereafter continue to decrease.

As we show in Table 8B & 8C, we find the highest significant abnormal return (0.15% per week) for the top portfolio (Q10) in week two, which translates into an abnormal return of 7.9% on a yearly basis. The weekly abnormal return for the long-short portfolio is insignificant for both week one and two, but equivalent to 1.9% (week one) and 3.3% (week two) on a yearly basis. Thus, a long position in portfolio Q10 week two generates both the

Table 9: RETURNS FOR TICKER SYMBOLS – U.S.

A. Raw returns per week by portfolio based on ASVI for different investment horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5
Q1	0.11%	0.35%	0.34%	0.34%	0.39%	0.35%
Q10	0.72%	0.41%	0.44%	0.37%	0.41%	0.35%
Q10-Q1	0.61%	0.07%	0.10%	0.03%	0.02%	0.00%

B. Abnormal return per week when investing *one* week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0012**	1.2075***	0.2766***	-0.0294	-0.1680***	86.55%
	(2.10)	(43.95)	(4.96)	(-0.49)	(-5.55)	
Q10	0.0019**	1.1900***	0.2135**	0.3156***	-0.3025***	69.73%
	(1.78)	(23.55)	(2.08)	(2.87)	(-5.43)	
Q10-Q1	0.0007	-0.0175	-0.0631	0.3450***	-0.1345**	5.14%
	(0.55)	(-0.30)	(-0.53)	(2.70)	(-2.07)	

C. Abnormal return per week when investing *two* weeks after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0011**	1.1890***	0.2156***	-0.0272	-0.0776**	83.24%
	(1.76)	(39.97)	(3.57)	(-0.42)	(-2.37)	
Q10	0.0022***	1.1713***	0.0751	0.2665***	-0.3353***	75.12%
	(2.37)	(27.05)	(0.85)	(2.83)	(-7.02)	
Q10-Q1	0.0011	-0.0176	-0.1406	0.2937**	-0.2577***	10.37%
	(0.93)	(-0.33)	(-1.28)	(2.50)	(-4.32)	

*In Table 9 we show returns for the U.S. market (S&P 500) when using ticker symbols as SVI measure. Table 9A shows weekly raw returns for different time-horizons for changes in search volume and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the stocks with the highest ASVI and Q1 contains the stocks with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we observe the ASVI, while Week 5 contains the raw returns five weeks after we observe the ASVI. In Table 9B and 9C we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model. Table 9B and 9C show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We have sorted the portfolios based on ASVI and invest one or two weeks after the observed ASVI. Number of observations: 512. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

highest and most significant alpha for the U.S. market when using company names as SVI measure.

In Table 9A we show the difference in raw returns between the portfolio including stocks with high ASVI (Q10) and low ASVI (Q1) for the U.S. market when using ticker symbols as SVI measure. In line with the raw returns for U.S. company names, we observe the highest raw returns for portfolio (Q10) and the long-short portfolio(Q10-Q1) the same week as we observe the ASVI (week zero). In addition, we find a positive raw return the following two weeks before the return flattens out towards zero in week three to five, similar to the reversal we identified for the U.S. when using company names as SVI measure.

As we show in Table 9B & 9C, we find the highest significant abnormal return (0,22% per week) for the top portfolio (Q10) in week two, equivalent to a yearly abnormal return of 12.3%. This is in line with our findings for the U.S. market when using company names as SVI measure, but 4.4% higher when using ticker symbols. The weekly abnormal return for the long-short portfolio is insignificant for both week one and two, but equivalent to 3.7% (week one) and 5.8% (week two) on a yearly basis, which is also higher compared to using company names for the U.S. market. Thus, for the U.S. market when using both company names and ticker symbols as SVI measure, a long position in portfolio Q10 week two generates both the highest and most significant alpha.

Table 10: RETURNS FOR COMPANY NAMES - EUROPE

A. Raw returns per month by portfolio based on ASVI for different investment horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4
Q1	0.66%	1.00%	1.12%	1.11%	0.96%
Q10	1.09%	0.76%	1.09%	1.10%	1.19%
Q10-Q1	0.43%	-0.24%	-0.03%	-0.01%	0.24%

B. Abnormal return per month when investing *one* week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0069**	0.6801***	0.2191	0.1925	-0.1834**	67.44%
	(2.16)	(10.37)	(1.36)	(1.09)	(-2.08)	
Q10	0.0051*	0.6317***	0.4630***	0.0983	-0.2535***	63.64%
	(1.55)	(9.22)	(2.74)	(0.53)	(-2.75)	
Q10-Q1	-0.0017	-0.0483	0.2440**	-0.0942	-0.0701	7.58%
	(-0.81)	(-1.10)	(2.25)	(-0.80)	(-1.18)	

C. Abnormal return per month when investing *two* weeks after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0081***	0.6513***	0.3098*	0.1838	-0.1777*	63.56%
	(2.43)	(9.47)	(1.83)	(0.99)	(-1.92)	
Q10	0.0081***	0.6896***	0.2381	-0.0054	-0.2502***	68.07%
	(2.63)	(10.83)	(1.52)	(-0.03)	(-2.92)	
Q10-Q1	0.0000	0.0384	-0.0717	-0.1892	-0.0725	2.63%
	(0.00)	(0.80)	(-0.61)	(-1.47)	(-1.12)	

*In Table 10 we show returns for the European market (S&P Europe 350) when using company names as SVI measure. Table 10A shows monthly raw returns for different time-horizons changes in search volume and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the stocks with the highest ASVI and Q1 contains the stocks with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we observe the ASVI, while Week 5 contains the raw returns five weeks after we observe the ASVI. In Table 10B and 10C we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model. Table XB and X show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We have sorted the portfolios based on ASVI and invest one or two weeks after the observed ASVI. Number of observations: 117. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 10A we show the difference in raw returns between the portfolio including stocks with high ASVI (Q10) and low ASVI (Q1) for the European market when using company names as SVI measure. As Table 10A shows, we find the highest positive raw return for portfolio (Q10) and the long-short portfolio (Q10-Q1) the same week as we observe the ASVI (week zero), but in contrast to the U.S. market, this is followed by a negative raw return in week one to three.

As we show in Table 10B & 10C, we find the highest significant abnormal return (0.81% per month) for the top portfolio (Q10) in week two, equivalent to a yearly abnormal return of 10.1%. This is in line with our findings for the U.S. market. However, for week one we find a higher abnormal return for portfolio Q1 and for week two the abnormal return is almost identical for portfolio Q10 and Q1. Thus, we cannot be certain that these abnormal returns are higher for portfolio Q10 than for portfolio Q1, which is confirmed by the insignificant long-short portfolio for both week one and week two.

Table 11: RETURNS FOR TICKER SYMBOLS - EUROPE

A. Raw returns per month by portfolio based on ASVI for different investment horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4
Q1	0.71%	0.91%	0.92%	0.27%	0.67%
Q10	0.70%	1.03%	0.70%	1.18%	1.37%
Q10-Q1	-0.01%	0.12%	-0.22%	0.91%	0.69%

B. Abnormal return per month when investing *one* week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0069**	0.8777***	0.4068**	-0.1332	-0.4428***	71.70%
	(1.88)	(11.49)	(2.16)	(-0.65)	(-4.31)	
Q10	0.0069*	0.6942***	0.7731***	-0.0233	-0.1812	45.44%
	(1.39)	(6.73)	(3.05)	(-0.08)	(-1.31)	
Q10-Q1	0.0000	-0.1835**	0.3663*	0.1100	0.2616**	16.17%
	(0.00)	(-2.23)	(1.81)	(0.50)	(2.36)	

C. Abnormal return per month when investing *two* weeks after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0054	0.6599***	0.3689*	0.1300	-0.1048	52.78%
	(1.35)	(7.99)	(1.81)	(0.58)	(-0.94)	
Q10	0.0040	0.7943***	0.1181	-0.1693	-0.2938***	66.95%
	(1.15)	(11.04)	(0.67)	(-0.87)	(-3.04)	
Q10-Q1	-0.0014	0.1344	-0.2508	-0.2993	-0.1890*	7.04%
	(-0.36)	(1.65)	(-1.25)	(-1.37)	(-1.72)	

*In Table 11 we show returns for the European market (S&P Europe 350) when using ticker symbols as SVI measure. Table 11A shows monthly raw returns for different time-horizons changes in search volume and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the stocks with the highest ASVI and Q1 contains the stocks with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we observe the ASVI, while Week 5 contains the raw returns five weeks after we observe the ASVI. In Table 11B and 11C we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model. Table 11B and 11C show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R Square for the model. We have sorted the portfolios based on ASVI and invest one or two weeks after the observed ASVI. Number of observations: 117. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 11A we show the difference in raw returns between the portfolio including stocks with high ASVI (Q10) and low ASVI (Q1) for the European market when using ticker symbols as SVI measure. As Table 11A shows, we see the highest positive raw return for portfolio Q10 and the long-short portfolio (Q10-Q1) three and four weeks after we observe the ASVI, while the raw return the same week is close to zero. This contradicts our previous findings since it does not follow the same pattern at all. However, noticeable is that when we use ticker symbols for the European market, we have a large amount of missing values which reduces the portfolio diversification for several weeks to a level below ten companies per portfolio, which makes us question this particular finding.

As we show in Table 11B & 11C, we find no significant abnormal return for the top portfolio (Q10) or for the long-short portfolio (Q10-Q1). In contrast to our previous findings, we find an alpha that is negative or close to zero – however insignificant – for the long-short portfolio. For week one, we also find a significant abnormal return for portfolio Q1, but we cannot be certain that this abnormal return is higher than for portfolio Q10, as the long-short portfolio is insignificant.

4.3 Does the predictive power of online search volume differ between market states?

In order to answer our third research question, if the predictive power of ASVI differ between bull and bear markets, we split our sample into three sub-periods based on bull and bear market characteristics. Our findings indicate that ASVI is able to better predict trading volumes and abnormal returns in bear markets than in bull markets. In the bear market period, we find that ASVI can predict abnormal trading volumes of up to 51% the following week for the U.S. market when using ticker symbols as SVI measure. For the U.S. market, we find a significant positive abnormal return in the first bull period (2005-2007) for the top portfolio Q10 using ticker symbols as SVI measure. In addition, we find economically substantial and significant (at the 10% level) abnormal returns in bear markets for our long-short portfolios for Europe using both company names and ticker symbols, indicating that using ASVI as a predictor of abnormal returns can be more economically substantial under bear market conditions.

4.3.1 Abnormal trading volume by market states

In Table 12, we show the difference in abnormal trading volume (ATV) between portfolios including stocks with high ASVI (Q10) and low ASVI (Q1) for each market and SVI measure. The ATV is measured one week after we observe the ASVI. We find a positive and significant abnormal trading volume for the long-short portfolio (Q10-Q1) in both markets and for both SVI measures, which is substantially higher in bear markets than bull markets. For bear markets in the U.S. we find that ASVI can predict an ATV of up to 51% the following week (using ticker symbols as SVI measure) and for Europe we find an ATV of up to 22% (using company names as SVI measure). This is in line with our previous findings that ASVI works better to predict ATV for the U.S. than for the European market.

Table 12: ABNORMAL TRADING VOLUME BY MARKET STATES

	U.S. Company names		U.S. Ticker symbols		Europe Company names		Europe Ticker symbols	
Market state	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
Q1	5.4%	57.9%	5.8%	49.1%	-12.3%	12.8%	-10.1%	13.8%
Q2	4.9%	58.2%	4.3%	51.5%	-11.6%	14.2%	1.2%	10.1%
Q3	5.5%	58.7%	4.5%	46.1%	-9.3%	17.5%	-9.5%	9.6%
Q4	6.2%	55.7%	4.0%	50.6%	-9.7%	21.0%	-9.4%	11.5%
Q5	6.2%	61.4%	4.9%	51.0%	-7.9%	18.5%	-12.4%	15.1%
Q6	6.1%	62.1%	4.2%	58.8%	-4.2%	17.0%	-7.6%	16.9%
Q7	6.5%	58.3%	7.2%	49.6%	-0.5%	20.0%	-9.9%	15.0%
Q8	5.9%	61.1%	6.5%	58.0%	-6.9%	17.2%	-11.2%	14.3%
Q9	7.3%	60.1%	10.5%	68.3%	-9.0%	15.8%	-10.3%	11.7%
Q10	15.8%	91.9%	22.0%	100.3%	-4.3%	35.1%	-6.4%	20.6%
Q10-Q1	10.4%	34.0%	16.2%	51.2%	8.0%	22.3%	3.7%	6.8%

In Table 12 we show the average trading volume per portfolio split by market, SVI measure and market state. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. The weekly abnormal trading volume (ATV) is computed as $ATV = (TV_{i,t} - TV_{i,avg}) / (TV_{i,avg})$, where $TV_{i,t}$ is the trading volume for firm i during week t and $TV_{i,avg}$ is the average of the weekly trading volume during all previous weeks in the sampling period. We then calculate the abnormal trading volume per week to get the average abnormal trading volume per portfolio. All values for our long-short portfolio Q10-Q1 in the table are significant at the 5% level or less.

Table 13: RETURNS BY MARKET STATE

A. Raw returns per year by market state when investing one week after observed ASVI

Market	SVI type	Portfolio	Bull (2004-2007)	Bear (2007-2009)	Bull (2009-2014)
U.S.	Company names	*Q10*	18%	-30%	32%
U.S.	Company names	*Q10-Q1*	2%	8%	1%
U.S.	Ticker symbols	*Q10*	29%	-29%	38%
U.S.	Ticker symbols	*Q10-Q1*	4%	22%	-1%
Europe	Company names	*Q10*	22%	-37%	18%
Europe	Company names	*Q10-Q1*	-5%	8%	-4%
Europe	Ticker symbols	*Q10*	28%	-29%	19%
Europe	Ticker symbols	*Q10-Q1*	-1%	44%	-6%

B. Abnormal returns per year by market state when investing one week after observed ASVI

Market	SVI type	Portfolio	Bull (2004-2007)	Bear (2007-2009)	Bull (2009-2014)
U.S.	Company names	Q10	4.2%*	28.6 %**	2.70%
U.S.	Company names	Q10-Q1	1.00%	12.70%	1.10%
U.S.	Ticker symbols	Q10	13.9 %***	44.40%	5.50%
U.S.	Ticker symbols	Q10-Q1	4.60%	40%	0.10%
Europe	Company names	Q10	-8.70%	18.50%	8.9%*
Europe	Company names	Q10-Q1	-5.30%	17.8%*	-3.60%
Europe	Ticker symbols	Q10	-9.00%	37.50%	8.4%.
Europe	Ticker symbols	Q10-Q1	-5.50%	36.4%*	-3.40%

*In Table 13 we show returns per market and SVI measure split by markets states. Table 13A shows yearly raw returns by market state for portfolios sorted on Abnormal Search Volume Index (ASVI). In Table 13B we show the abnormal returns per portfolio split by market state, risk-adjusted using the Carhart four-factor model. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

4.3.2 Abnormal returns by market states

As we show in Table 13B, we find substantially higher – but less significant – abnormal returns in the bear market period for both markets and SVI measures when we divide our sample into three different sub-periods. In line with our previous findings for the whole ten year period, we find the highest abnormal returns for the U.S. market when using ticker symbols as SVI measure for the bull period (2005-2007). In the bear period (2007-2009), we find a significant positive abnormal return of 28.6% (significant on 5 % level) for the U.S. market when using company names as SVI measure for the top portfolio Q10. We also find that the long-short portfolios for Europe in the bear period, using both company names and ticker symbols as SVI measure, generates abnormal returns of 17.8% and 36.4% respectively (significant at the 10% level). Overall the significance levels are lower when splitting up our sample into different time periods, which probably can be explained by the lower number of observations for each portfolio. In contrast to our findings for the whole ten year period, it is noteworthy that both the top portfolios (Q10) and the long-short portfolios (Q10-Q1) are positive and economically substantial in the bear period for both markets and SVI measures (however with an overall low significance). What is also remarkable is that abnormal returns in bull markets for the U.S. has diminished compared to the full ten-year period, and that the abnormal return is much lower and insignificant in the last bull market period (2009-2014).

Table 14: U.S. COMPANY NAMES BY MARKET STATES

A. Weekly abnormal return per portfolio for S&P 500 during the Bull period (2004-2007) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0006	1.0108***	0.3091***	-0.0235	0.0580	90.72%
	(1.22)	(27.75)	(5.23)	(-0.30)	(1.29)	
Q10	0.0008*	1.0559***	0.1178*	0.0365	0.0919*	88.73%
	(1.45)	(26.25)	(1.80)	(0.43)	(1.86)	
Q10-Q1	0.0002	0.0451	-0.1913**	0.0600	0.0339	4.07%
	(0.25)	(0.83)	(-2.16)	(0.52)	(0.51)	

B. Weekly abnormal return per portfolio for S&P 500 during the Bear period (2007-2009) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0026	1.1035***	0.3785**	0.2163	-0.2311**	90.45%
	(1.05)	(14.93)	(2.37)	(1.29)	(-2.57)	
Q10	0.0049**	1.2133***	0.0627	0.2297	-0.1380	87.88%
	(1.71)	(14.04)	(0.34)	(1.17)	(-1.32)	
Q10-Q1	0.0023	0.1099	-0.3159	0.0134	0.0931	6.22%
	(0.74)	(1.17)	(-1.56)	(0.06)	(0.82)	

C. Weekly abnormal return per portfolio for S&P 500 during the Bull period (2009-2014) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0003	1.1031***	0.1551***	0.0541	-0.1502***	90.11%
	(0.54)	(38.87)	(2.85)	(0.96)	(-5.14)	
Q10	0.0005	1.0662***	0.2324***	0.2089***	-0.1548***	88.49%
	(0.84)	(33.88)	(3.85)	(3.33)	(-4.78)	
Q10-Q1	0.0002	-0.0369	0.0773	0.1549*	-0.0045	1.74%
	(0.28)	(-0.91)	(0.99)	(1.91)	(-0.11)	

*In Table 14 we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model, for the Bull period (2004-2007), the Bear period (2007-2009) and the Bull period (2009-2014). The tables show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. Number of observations in A: 138. Number of observations in B: 70. Number of observations in C: 304. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 14 we show the abnormal returns by market states between portfolios including stocks with high ASVI (Q10) and low ASVI (Q1) for the U.S. market when using company names as SVI measure. For the bear market period, we find a significant positive abnormal return for the top portfolio (Q10) of 0.49% per week, equivalent to a yearly abnormal return of 28.6%. For the top portfolio in the two bull market periods, we find that the abnormal returns observed for the whole ten-year period are less significant and almost eliminated during the last bull market period.

Table 15: U.S. TICKER SYMBOLS BY MARKET STATES

A. Weekly abnormal return per portfolio for S&P 500 during the Bull period (2004-2007) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0016**	1.2298***	0.2694**	-0.0020	0.0305	78.19%
	(1.72)	(17.42)	(2.35)	(-0.01)	(0.35)	
Q10	0.0025***	0.9994***	0.0791	-0.6868***	0.2710***	70.05%
	(2.42)	(13.02)	(0.63)	(-4.22)	(2.87)	
Q10-Q1	0.0009	-0.2303**	-0.1903	-0.6848***	0.2405*	9.16%
	(0.56)	(-2.01)	(-1.02)	(-2.82)	(1.70)	

B. Weekly abnormal return per portfolio for S&P 500 during the Bear period (2007-2009) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0006	1.1944***	0.5888***	-0.2006	-0.2418***	91.14%
	(0.26)	(17.01)	(3.88)	(-1.26)	(-2.84)	
Q10	0.0071	1.2271***	0.6291	0.9137**	-0.2952	72.65%
	(1.18)	(6.70)	(1.59)	(2.20)	(-1.33)	
Q10-Q1	0.0065	0.0327	0.0403	1.1143**	-0.0534	21.61%
	(1.03)	(0.17)	(0.10)	(2.57)	(-0.23)	

Table X: Weekly abnormal return per portfolio for S&P 500 during the Bull period (2009-2014) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0010*	1.2266***	0.0994	-0.0035	-0.1616***	85.42%
	(1.37)	(31.93)	(1.35)	(-0.05)	(-4.09)	
Q10	0.0010	1.1738***	0.0392	0.1079	-0.2002***	73.10%
	(0.96)	(21.13)	(0.37)	(0.97)	(-3.50)	
Q10-Q1	0.0000	-0.0528	-0.0602	0.1114	-0.0386	0.78%
	(0.01)	(-0.73)	(-0.43)	(0.77)	(-0.51)	

*In Table 15 we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model, for the Bull period (2004-2007), the Bear period (2007-2009) and the Bull period (2009-2014). The tables show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. Number of observations in A: 138. Number of observations in B: 70. Number of observations in C: 304. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 15 we show the abnormal returns by market states between portfolios including stocks with high ASVI (Q10) and low ASVI (Q1) for the U.S. market when using ticker symbols as SVI measure. In the first bull market period, we find a significant positive abnormal return for the top portfolio Q10 of 0.25% per week, equivalent to a yearly abnormal return of 13.9%. For the bear market period and for the second bull market period, we find no significant abnormal returns. However, the insignificant abnormal returns in the bear market period are still noteworthy for the top portfolio Q10 (0.71%, equivalent to 44.4% on a yearly basis) and for the long-short portfolio Q10-Q1 (0.65%, equivalent to 40.0% on a yearly basis), since it indicates that it can be economically substantial. As for U.S. company names, we find that both the top portfolio (Q10) and the long-short portfolio (Q10-Q1) are higher and more significant in the first bull market compared to the second bull period for U.S tickers.

Table 16: EUROPEAN COMPANY NAMES BY MARKET STATES

A. Monthly abnormal return per portfolio for S&P Europe 350 during the Bull period (2004-2007) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	-0.0030	0.3620	-0.3990	1.7784**	0.5439	46.19%
	(-0.46)	(1.42)	(-1.16)	(2.68)	(1.33)	
Q10	-0.0075	0.1545	0.0116	1.6401**	0.8347*	45.24%
	(-1.11)	(0.60)	(0.03)	(2.42)	(2.00)	
Q10-Q1	-0.0045	-0.2075	0.4106*	-0.1383	0.2908	19.63%
	(-1.04)	(-1.26)	(1.84)	(-0.32)	(1.10)	

B. Monthly abnormal return per portfolio for S&P Europe 350 during the Bear period (2007-2009) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0005	0.5516**	0.5553	-0.6471	-0.8363**	78.25%
	(0.04)	(3.06)	(1.36)	(-0.99)	(-2.52)	
Q10	0.0143	0.5946***	0.6834*	-1.0476	-1.1472***	85.81%
	(1.28)	(3.61)	(1.84)	(-1.76)	(-3.80)	
Q10-Q1	0.0138*	0.0430	0.1281	-0.4005	-0.3109	19.33%
	(1.37)	(0.29)	(0.38)	(-0.75)	(-1.14)	

C. Monthly abnormal return per portfolio for S&P Europe 350 during the Bull period (2009-2014) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0101***	0.6109***	0.0164	0.3442*	-0.1347	67.84%
	(2.47)	(6.80)	(0.08)	(1.73)	(-1.36)	
Q10	0.0071*	0.5475***	0.2321	0.2835	-0.1948*	62.11%
	(1.65)	(5.79)	(1.01)	(1.36)	(-1.87)	
Q10-Q1	-0.0030	-0.0634	0.2158	-0.0607	-0.0601	7.95%
	(-1.08)	(-1.03)	(1.45)	(-0.45)	(-0.88)	

*In Table 16 we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model, for the Bull period (2004-2007), the Bear period (2007-2009) and the Bull period (2009-2014). The tables show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. Number of observations in A: 31. Number of observations in B: 16. Number of observations in C: 70. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 16 we show the abnormal returns by market states between portfolios including stocks with high ASVI (Q10) and low ASVI (Q1) for the European market when using company names as SVI measure. For the bear market period (2007-2009), we find a significant (only at the 10% level) positive abnormal return of 1.38% per month (equivalent to 17.8% on a yearly basis) for the long-short portfolio (Q10-Q1). The low significance can probably be explained by the low number of observations when we split up our sample in different periods, in particular for the short bull market period. However, for the two bull market periods we find no abnormal returns for the long-short portfolio. During the last bull period (2009-2014), we find that the bottom portfolio Q1 generates a significant abnormal return of 1.01% per month, which is contrary to our previous findings.

Table 17: EUROPEAN TICKER SYMBOLS BY MARKET STATES

A. Monthly abnormal return per portfolio for S&P Europe 350 during the Bull period (2004-2007) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0096**	0.7747***	0.2409	-0.0392	-0.4576***	69.20%
	(1.93)	(7.09)	(0.91)	(-0.16)	(-3.79)	
Q10	-0.0078	0.5152	-0.4886	2.4408***	0.5512	46.45%
	(-0.91)	(1.56)	(-1.10)	(2.83)	(1.04)	
Q10-Q1	-0.0047	-0.1461	-0.4150	1.1879*	0.1506	14.58%
	(-0.74)	(-0.60)	(-1.27)	(1.89)	(0.39)	

B. Monthly abnormal return per portfolio for S&P Europe 350 during the Bear period (2007-2009) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0007	0.8225***	0.5271	-0.6843	-0.8736*	79.80%
	(0.05)	(3.67)	(1.04)	(-0.84)	(-2.12)	
Q10	0.0269	0.7100*	1.9020**	-1.9700	-1.0862	66.62%
	(1.05)	(1.87)	(2.22)	(-1.43)	(-1.56)	
Q10-Q1	0.0262*	-0.1125	1.3749*	-1.2857	-0.2127	52.84%
	(1.39)	(-0.40)	(2.18)	(-1.27)	(-0.42)	

C. Monthly abnormal return per portfolio for S&P Europe 350 during the Bull period (2009-2014) when investing one week after observed ASVI

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	*R^2 (%)*
Q1	0.0096**	0.7747***	0.2409	-0.0392	-0.4576***	69.20%
	(1.93)	(7.09)	(0.91)	(-0.16)	(-3.79)	
Q10	0.0068	0.5978***	0.2241	0.2933	-0.1327	51.45%
	(1.23)	(4.95)	(0.77)	(1.10)	(-1.00)	
Q10-Q1	-0.0029	-0.1770*	-0.0168	0.3325	0.3248***	18.95%
	(-0.61)	(-1.71)	(-0.07)	(1.45)	(2.85)	

*In Table 17 we show the abnormal returns per portfolio, risk-adjusted using the Carhart four-factor model, for the Bull period (2004-2007), the Bear period (2007-2009) and the Bull period (2009-2014). The tables show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. Number of observations in A: 31. Number of observations in B: 16. Number of observations in C: 70. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

In Table 17 we show the abnormal returns by market states between portfolios including stocks with high ASVI (Q10) and low ASVI (Q1) for the European market when using ticker symbols as SVI measure. We find no significant abnormal return for the top portfolio during any of the three periods. However, in line with our findings for European company names in the bear market period, we find a significant (at the 10% level) positive abnormal return for the long-short portfolio Q10-Q1 of 2.62% per month (equivalent to 36.4% on a yearly basis) for the bear market period (2007-2009). Although these abnormal returns during the bear period are only significant at the 10% level, they are still very interesting since they can be economically substantial. The low significance can probably be explained by the low number of observations when we split our sample in different periods, in particular for the short bull market period.

Table 18: ABNORMAL RETURNS USING DIFFERENT ASSET PRICING MODELS

	U.S Ticker Symbols			U.S Company Names		
	Q10	*Q1*	*Q10 - Q1*	*Q10*	*Q1*	*Q10 - Q1*
CAPM	8.87%*	6.08%**	2.64%	4.34%*	1.90%	2.30%
	(1.410)	(1.820)	(0.386)	(1.405)	(0.839)	(0.573)
Fama & French	9.75%	6.22%**	3.32%	4.82%**	2.70%	0.50%
	(1.591)	(0.058)	(0.492)	(1.628)	(1.026)	(0.599)
Carhart	10.63%**	6.70%**	3.69%	5.23 %**	3.20%*	1.90%
	(1.776)	(0.203)	(0.547)	(1.809)	(1.274)	(0.570)

	Europe Ticker Symbols			Europe Company Names		
	Q10	*Q1*	*Q10 -Q1*	*Q10*	*Q1*	*Q10 -Q1*
CAPM	6.70%	3.63%	2.97%	3.25%	5.98%**	-2.58%
	(1.087)	(0.766)	(0.621)	(0.787)	(1.689)	(-1.042)
Fama & French	6.60%	3.77%	2.74%	3.59%	6.50%**	-2.75%
	(1.103)	(0.802)	(0.573)	(0.890)	(1.689)	(-1.126)
Carhart	8.62%*	8.63%*	0.00%	6.34%*	8.54%***	-2.04%
	(1.388)	(1.876)	(-0.002)	(1.551)	(2.164)	(-0.809)

*Table 18 presents the risk-adjusted return regressed using the CAPM, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model separately. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. The long-short portfolio (Q10-Q1) show the differences between the top and bottom portfolio. We focus on the abnormal return (α) that in the CAPM model is adjusted for the Market-Risk factor (Mkt-RF). In the Fama and French (1993) three-factor model the (SMB) and the value factor (HML) are added to the CAPM model. Finally, the Carhart (1997) four-factor model also adjusts for the momentum factor (UMD). T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

4.4 Robustness

In addition to controlling for different time periods by market states, we examine the robustness in our findings by testing additional variations of abnormal search volume (ASVI), by changing the number of portfolios and by testing three different asset pricing models.

First, we alter the measurement of expected search volume (SVI), and thus abnormal search volume (ASVI), in a number of different ways. In addition to using the median of the prior eight weeks as the expected search volume, we also test (i) the mean of the prior eight weeks, (ii) the median of the prior four weeks, (iii) search volume from the prior week, and (iv) the mean of the whole prior time series. We find that the median of the prior eight weeks is more robust to one-week peaks and drops in search volume compared to (i), (ii) and (iii). However, we get similar results using all four alternative measures with positive abnormal returns for portfolio Q10 the first two weeks for the U.S. market and an insignificant, but positive, abnormal return for the long-short portfolio (Q10-Q1).

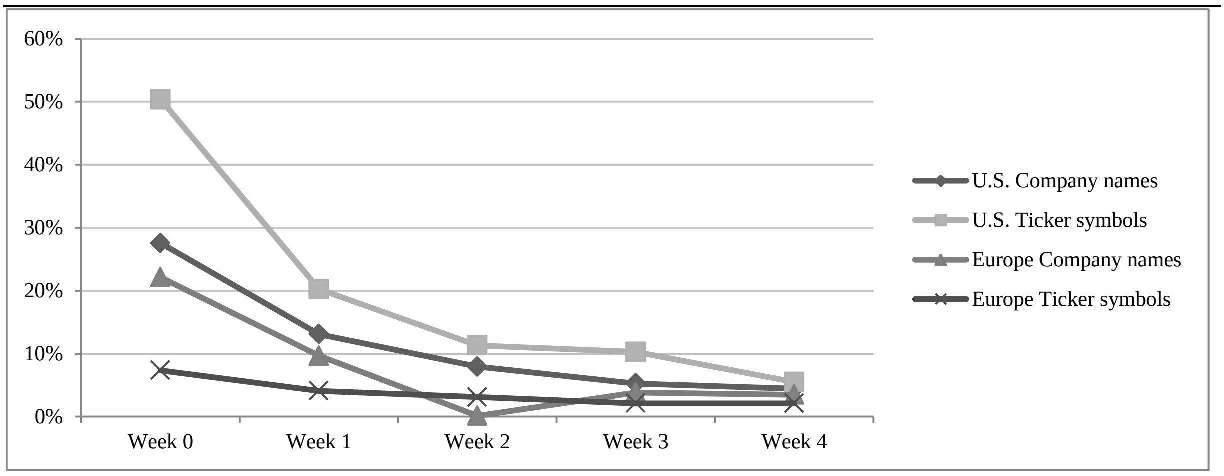
Second, we alter the number of quintiles forming the portfolios. In addition to testing ten portfolios, we also sort the stocks into five and 20 portfolios based on ASVI. We anticipate a slightly lower ASVI variation between the portfolios when using five quintiles and a higher ASVI variation when using 20 quintiles. Thus, if ASVI can predict abnormal trading volume and returns, we should observe a larger spread between the top and bottom portfolio when using 20 quintiles compared to ten. However, we find no major differences when using five or 20 portfolios and we therefore find our results to be robust against the choice of portfolio formation. In order to have properly diversified portfolios in which the company-specific risk is eliminated, there should be at least 15-20 stocks in each portfolio according to Elton & Gruber (1977). However, when sorting our stocks into 20 quintiles, for some weeks we get less than 10 stocks per portfolio for the samples with the highest amount of missing values, thus reducing the validity of the results for 20 portfolios.

Third, we test alternative definitions of abnormal returns using three different asset pricing models, namely the capital asset pricing model (CAPM), the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. As we show in Table 19, the alpha values are positive for all of the models, except for the long-short portfolio (Q10-Q1) when using company names as SVI measure for Europe. We also find that the abnormal returns increase for each model extension, i.e. receiving the highest abnormal return using the Carhart four-factor model for the majority of our samples.

5. DISCUSSION

Our empirical findings show that investor attention, measured by online search volume in Google, can predict abnormal trading volumes both for the U.S. and the European market. However, to what extent online search volume can predict abnormal returns differs between geographies, bull and bear markets, and SVI measures. In addition, the observed abnormal returns will likely diminish or be completely eliminated when accounting for trading costs related to rebalancing the portfolios on a weekly basis. For the U.S. market, our findings are in line with the price pressure hypothesis by Barber & Odean (2008), the findings of Da et al. (2011) and Joseph et al. (2011). Our findings also indicate that search volume can predict abnormal returns that are more economically substantial (however less significant) in bear market periods compared to

Figure 3: WEEKLY DIFFERENCE IN ABNORMAL TRADING VOLUME BETWEEN PORTFOLIO Q10 AND Q1



In Figure 3 we show the difference in abnormal trading volume between the portfolio with the highest and lowest ASVI (i.e. portfolio Q10 minus Q1) by different time-horizons between ASVI and ATV. Week 0 contains the ATV the same week as we observe the ASVI, while Week 4 contains the ATV four weeks after we see the ASVI change and rebalance the portfolios. The weekly abnormal trading volume (ATV) is computed as ATV = $(TV_{i,t} - TV_{i,avg}) / (TV_{i,avg})$*, where* $TV_{i,t}$ *is the trading volume for firm i during week t and* $TV_{i,avg}$ *is the average of the weekly trading volume during all previous weeks in the sampling period. We then calculate the abnormal trading volume per week to get the average abnormal trading volume per portfolio, and compute the difference between portfolio Q10 and Q1 to get the values for each time horizon.*

the whole ten-year period. We also find that the abnormal returns observed in the pre-crisis period are almost non-existent in the post-crisis period, which could be a sign that the market has become more efficient. This finding also support our suspicions regarding previous studies, i.e. that the observed abnormal returns over a longer period of time can be derived to a large degree from the financial crisis and the period before the online search data was not publicly available.

5.1 Trading volume

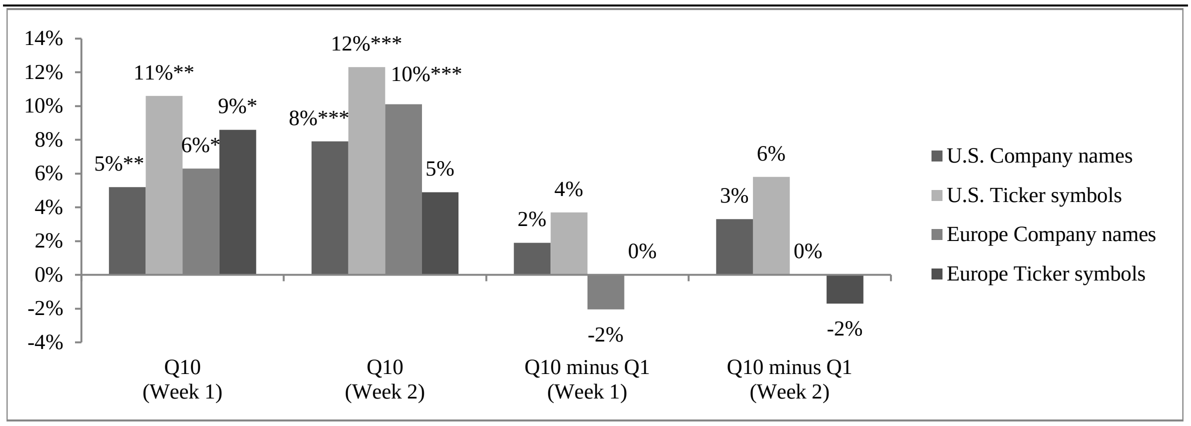
We find a positive and significant relationship between abnormal search volume (ASVI) and abnormal trading volume (ATV) for both the U.S. and the European market. We find that ASVI can predict higher ATV for the U.S. market, and higher ATV when using ticker symbols as SVI measure compared to company names. Our findings indicate that particularly search volume for ticker symbols can be used to reveal and quantify the interest of investors, which reinforces the findings of Da et al. (2011) and Joseph et al. (2011).

As we show in Figure 3, when we form portfolios based on abnormal search volume (ASVI) from the prior week, we find that ASVI can predict an abnormal trading volume (ATV) of between 4 % and 20% the following week (week 1). We observe similar patterns for the second week, after which the ATV gradually levels out towards zero. Our findings are consistent for searches on both company names and ticker symbols, as well as for both the U.S. and the European market. This implies that ASVI can predict changes in trading volume, and thus liquidity, for the following two weeks by looking at changes in online search volumes, which is in line with previous findings of Da et al. (2011) and Joseph et al. (2011)

5.2 Abnormal returns

Our findings for the whole ten-year period show that abnormal search volume (ASVI) can help predict increases in raw returns as well as positive abnormal returns for the two weeks following the observed ASVI. In line with the price pressure hypothesis by Barber & Odean (2008), our findings indicate that investor attention can help predict attention-grabbing stocks that are subject to net buying and thus a short-term price increase. In similarity with Da et al. (2011), we find that for a portfolio

Figure 4: ABNORMAL RETURN PER YEAR BY MARKET AND SVI MEASURE



*In Figure 4 we show a summary of yearly abnormal return (alpha) per sample and portfolio, after adjusting returns for risk factors using the Carhart four-factor model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) and each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. We then measure returns either one or two weeks after we observe the ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

including stocks with high ASVI, a two-week increase in returns for the U.S. market followed by a reversal in week three can be observed. As we show in Figure 4, we find higher and more significant positive abnormal returns for a long position in the portfolio including stocks with high ASVI (Q10) than for the long-short portfolio (Q10-Q1). These findings are consistent with Joseph et al. (2011), who show that ASVI can predict abnormal risk-adjusted returns by using the Carhart (1997) four-factor model for the U.S. market.

We provide three alternative explanations for the observed short-term increase in abnormal returns. First, increased investor attention can imply additional noise into prices that makes markets less efficient (Da et al., 2011). Trading by not fully rational investors, acting based on their beliefs or sentiments not fully justified by fundamental information, can push stock prices away from their fundamental values and when uninformed investors actively buy, assets become temporarily overpriced (Barber et al., 2009). These so-called noise traders make markets less efficient by moving prices away from their fundamental values. However, stock prices changed by noise traders tend to revert back towards its value over time (Black, 1986), which is precisely what we observe after the two-week increase in the U.S. market. Second, investor attention can also imply more informed investors and thus more efficient markets (Aouadi et al., 2013). As we find a positive relationship between online searches and trading volume, we can interpret this as search engines help reducing information asymmetry which results in increased willingness to invest from investors leading to a short-term price pressure (Bank et al., 2011). The price reversal can subsequently be seen as an adjustment in compensation for risk. When companies are being more searched, the stocks will have lower returns in the long term, as investors will require less returns as compensation for risk associated with information asymmetry (Merton, 1987). Third, Grossman & Stiglitz (1980) argue that the returns should not be considered as abnormal, but rather as the cost for collecting information. These returns are considered to compensate investors for expenses associated with gathering and processing information, and when accounting properly for these expenses the returns are no longer abnormal.

Our finding that ASVI seems to be slightly better at predicting positive abnormal returns for the U.S. market (S&P 500) than for the European market (S&P Europe 350) is also interesting. One potential explanation is the fact that the U.S. is a more homogenous market, where the listed companies on the S&P 500 are better known for a larger audience of retail investors. Language and different online search behaviour between the U.S. and Europe may also influence the ability to predict both abnormal trading volume and returns for the different markets.

5.3 Market states

Before discussing our findings when controlling for different market states, we want to underline that few of these results are statistically significant, probably explained by the lower number of observations when we split our sample into sub-periods. However, we still consider these findings to be interesting since they could be economically substantial and should be of interest to further examine in future research related to investor attention and online search.

We find that abnormal returns differ greatly depending on market state when we divide our sample into three different sub-periods. We find that abnormal returns are significantly higher – although less significant – in the bear market period compared the bull market periods and to the full ten-year period. For the U.S. market, we find a significant positive yearly abnormal return for the top portfolio Q10 of 28.6% in the bear market period when using company names as SVI measure. For the

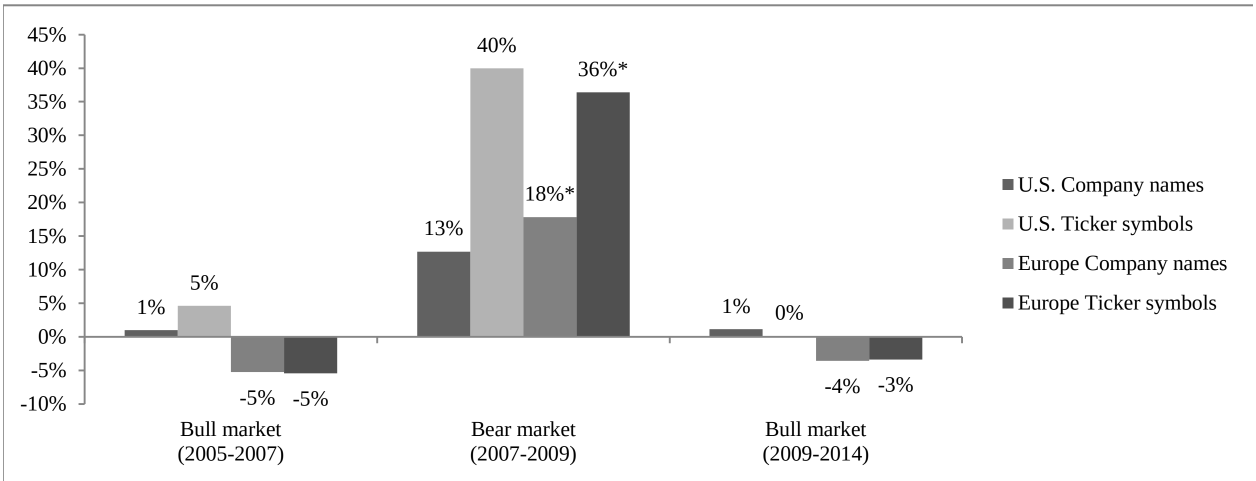
European market using a long-short portfolio (Q10-Q1), we find a positive abnormal return of 18% per year for company names and 36% per year for ticker symbols (significant at the 10% level) during the bear market period. This indicates that using changes in online search volume to predict abnormal returns works considerably better during periods of crisis (bear markets) than markets with positive prospects (bull markets). As we show in Figure 5, in the bear market period we can observe the same pattern for abnormal returns for both the U.S. market and European market, as well as for both SVI measures, which we were not able to find when looking at the full ten-year period.

Our findings of higher abnormal returns during the bear market period are in line with Gwilym et al. (2014) who find that trading strategies based on online searches can be particularly profitable during a financial crisis. In addition, as previous studies have pointed out, financial crises can adversely affect the efficiency of stock markets (Lim et al., 2008) which could be another explanation to the large differences between the market states.

The fact that we observe high abnormal returns following increases in search volume primarily during bear markets sheds new light on previous studies relating to investor attention and online search. Since our findings show that using online searches to predict abnormal returns works best – and perhaps only – in bear markets, it is not surprising that studies examining periods of which the financial crisis represents a major part of the sampling period observe abnormal returns.

Another interesting finding when splitting up our sample into different sub-periods is that we observe higher abnormal returns in the first bull period (2005-2007) than in the second bull period (2009-2014) for the U.S. market (S&P 500). This gives us reason to further question the findings in several previous studies using online search to predict abnormal returns (e.g. Da et al., 2011; Joseph et al., 2011), since large parts of their sampling periods are before Google made its online search data publicly available in May 2006. Thus, according to the semi-strong form of the efficient market hypothesis, only investors with private access to this information would have been able to earn the abnormal returns observed in these

Figure 5: ABNORMAL RETURN PER YEAR FOR THE LONG-SHORT PORTFOLIO Q10-Q1 BY MARKET STATE



*In Figure 5 we show yearly abnormal returns for the long-short portfolio Q10-Q1, i.e. the difference between the portfolio with highest and lowest ASVI during the previous week, by different market states. Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. We define a bull (bear) market as a positive (negative) change greater than 20% in the stock price index that lasts for at least three months. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

studies. Alternatively, this could also be interpreted as a sign that the market has become more efficient and that information is incorporated in market prices to a larger extent as information has become more easily accessible, for example by search engines such as Google and other technical features. This would imply that it is more difficult to find arbitrage opportunities today than a decade ago.

5.4 Limitations and future research

We have throughout the study pointed out limitations in relation to particular empirical choices, findings and interpretations. In this section we want to put forward additional general limitations that should be taken into consideration when interpreting the broader implications of our study.

Concerning our main findings, there are limitations in regards to sample exclusions and missing observations. When using searches for ticker symbols as a proxy for investor attention, we need to exclude a large amount of stocks in our sample due to ambiguity and too generic ticker symbols with multiple meanings. These exclusions are made manually based on information in Google Trends for each stock and search measure, and are thus prone to be affected by subjectivity. Missing values for search volume, i.e. when there are not sufficient online searches for a stock, also affects our sample and likely makes it biased towards well-known stocks. These two factors reduce our sample size to almost a quarter of the original sample in some cases and therefore weaken the generalizability of our findings.

A limitation in regards to our findings related to different market states is the fact that our sampling period only contains one bear market period. Although we find interesting and substantial differences between the market states, the findings might only hold for the particular financial crisis in our sample period. In addition, the bear period is rather short which leaves us with much fewer observations than for the two bull market periods, thus making it difficult to find significant relationships.

Finally, we also have limitations regarding access to data. As we only use public data, we can only access indexed search volume data for each stock since this is what Google provides to the public. This restricts our analysis to only compare relative search volumes between stocks, rather than absolute values. Access to values for absolute search volume would have enabled us to directly compare the investor recognition between stocks, instead of only the changes in investor attention. Furthermore, Google Trends only provides daily search volumes for the past three months, which restricts our analysis to weekly data. As we find the strongest relationship between search volume and stock measures the same week, it is possible that weekly search volume might hide peaks and drops in investor attention within the same week.

6. CONCLUSION

In this study we show that investor attention can help predict abnormal trading volumes and stock market returns, but that large differences between market states and geographies exist, which makes it difficult and unreliable for investors to exploit. While traditional studies of investor attention use indirect proxies such as media coverage, advertising expenses and analyst coverage, we employ a more direct measure by using online searches in Google for company names and ticker symbols as a proxy for investor attention related to a particular stock. We examine all stocks in the S&P 500 and S&P Europe 350 indices during the period 2005-2014 and control our results for market risk, size, value and momentum factors in accordance with the Carhart (1997) four-factor model.

First, we find a significant relationship between abnormal search volume (ASVI) and abnormal trading volume (ATV) for both the European and U.S. market. In particular, over a ten-year period, we find that search volume for ticker symbols in Google can predict abnormal trading volumes of up to 20% in the following week for the U.S. market. Our findings are consistent with previous research showing that investor attention can predict short-term trading volumes (e.g. Barber & Odean, 2008; Da et al., 2011). Over a ten-year period we find that online searches can predict both higher and more significant abnormal trading volumes for the U.S. market than for the European market.

Second, over a ten-year period we find that search volume in Google can predict yearly abnormal returns of up to 12% before trading costs for the U.S. market (S&P 500), by investing in a portfolio consisting of stocks with the highest increase in search volume for ticker symbols. Our findings of abnormal returns are in line with previous studies relating to investor attention and online searches for the U.S. market (e.g. Da et al., 2011). However, when adding trading costs and taxes, the observed abnormal returns will diminish and likely be eliminated in most cases. In addition, our findings for the European market (S&P Europe 350) are inconsistent and overall less significant when using the same method.

Third, we find that online search volume can predict considerably higher abnormal returns during the global financial crisis compared to the full ten-year period, indicating that the observed abnormal returns are only apparent during exceptional market conditions. While several previous studies show that online search can predict abnormal returns (e.g. Da et al., 2011; Joseph et al., 2011), we argue that these findings are a result of sampling periods including both the global financial crisis and periods when online search data was not yet made public, thus making their findings unsustainable and practically unfeasible for investors to exploit. This is supported by our findings, showing that the abnormal returns we observe for the pre-crisis period in the U.S. are almost non-existent in the post-crisis period.

In conclusion, our study contributes to the existing literature on investor attention by reinforcing the relevance of online searches and by providing a more comprehensive evaluation of how online searches relates to financial markets. We also give reason to further scrutinize previous and forthcoming studies relating to investor attention and online search as we provide new insights relating to bull and bear markets, geographical differences and alternative online search measures. Our findings suggest that using online search to predict abnormal returns might have worked during exceptional market circumstances, but that it is rather unreliable under normal market conditions and practically difficult for investors to exploit.

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APPENDIX

Exhibit A: Variable definitions

Variable	Definition
SVI - Search Volume Index	Search Volume Index aggregate search frequency from Google Trends based on stock ticker or company name
ASVI - Abnormal Search Volume Index	The log of SVI during the week minus the log of median SVI during the previous 8 weeks
ATV- Abnormal Trading Volume	Abnormal Trading Volume (TV_{it} - $TV_{i,avg}$) / (TV_{avg}), where TV_{it} is the trading volume for firm i during week t and $TV_{i,avg}$ is the average of the weekly trading volume during all previous weeks in the sampling period.
CAPM - Capital Asset Pricing Model	The CAPM model determines the appropriate required rate by adjusting for the Market-Risk factor (Rm-Rf).
The Fama-French (1993) Three-Factor model	The Fama and French (1993) Three-Factor model add the risk factor for size (SMB) and value (HML) to the CAPM- model.
Carhart (1997) Four Factor model	The Carhart (1997) Four-Factor model add the risk factor for momentum (UMD) to the Fama and French (1993) three-factor model
Rm-Rf, Market risk factor	The market risk factor is the value-weighted stock market return minus the one-month Treasury bill rate
SMB (Small Minus Big) - Size factor	SMB (Small Minus Big) is the average return on small portfolios minus the average return on big portfolios
HML (High Minus Low) - Value factor	HML (High minus Low) is the average return on two value portfolios minus the average return on growth portfolios
UMD (Up Minus Down) - Momentum factor	UMD – (Up Minus Down) is the average return on the higher prior return portfolios minus the average return on the lower prior return portfolios

Exhibit B: Abnormal returns for Week 1 & Week 2

Table B1: Weekly abnormal return per portfolio for S&P 500 using ASVI for company names from the previous week

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	R^2 (%)
Q1	0.0096**	1.0994***	0.2490***	0.1269***	-0.1831***	89.91%
	(1.27)	(49.59)	(5.53)	(2.63)	(-7.49)	
Q2	0.0007**	1.1194***	0.1738***	0.1001***	-0.1284***	94.50%
	(2.08)	(71.41)	(5.46)	(2.94)	(-7.43)	
Q3	0.0010***	1.0918***	0.1572***	0.0602*	-0.1523***	93.99%
	(2.94)	(68.06)	(4.82)	(1.73)	(-8.61)	
Q4	0.0006**	1.0743***	0.1503***	0.1247***	-0.1509***	94.88%
	(1.82)	(73.02)	(5.03)	(3.90)	(-9.30)	
Q5	0.0011***	1.0478***	0.1496***	0.1294***	-0.1564***	94.51%
	(3.53)	(70.02)	(4.92)	(3.98)	(-9.48)	
Q6	0.0005*	1.0764***	0.0974***	0.0091	-0.1414***	94.18%
	(1.64)	(70.64)	(3.15)	(0.27)	(-8.41)	
Q7	0.0009***	1.0700***	0.1774***	0.0531*	-0.1362***	94.73%
	(2.91)	(73.23)	(5.98)	(1.67)	(-8.46)	
Q8	0.0013***	1.0669***	0.1444***	0.0585*	-0.1106***	94.70%
	(4.18)	(73.89)	(4.92)	(1.86)	(-6.94)	
Q9	0.0007**	1.1065***	0.1451***	0.1615***	-0.0891***	93.71%
	(2.07)	(66.78)	(4.31)	(4.48)	(-4.88)	
Q10	0.0010**	1.1297***	0.1437***	0.2102***	-0.1470***	87.85%
	(1.81)	(45.16)	(2.83)	(3.86)	(-5.33)	
Q10-Q1	0.0004	0.0303	-0.1053*	0.0833	0.0361	1.20%
	(0.57)	(1.02)	(-1.74)	(1.29)	(1.10)	

Table B2: Weekly abnormal return per portfolio for S&P 500 using ASVI for company names from two weeks prior to investing

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	R^2 (%)
Q1	0.0096**	1.1275***	0.2394***	0.2173***	-0.1892***	90.57%
	(1.75)	(50.60)	(5.29)	(4.49)	(-7.70)	
Q2	0.0010***	1.0721***	0.1598***	0.0640*	-0.1567***	94.33%
	(2.97)	(69.77)	(5.12)	(1.92)	(-9.25)	
Q3	0.0008***	1.0744***	0.1908***	0.0709**	-0.1264***	94.67%
	(2.39)	(72.63)	(6.35)	(2.20)	(-7.75)	
Q4	0.0004*	1.0874***	0.1788***	0.1012***	-0.1452***	95.08%
	(1.34)	(74.94)	(6.07)	(3.21)	(-9.07)	
Q5	0.0007**	1.0997***	0.1430***	0.1285***	-0.1230***	94.75%
	(2.12)	(73.00)	(4.68)	(3.93)	(-7.41)	
Q6	0.0006**	1.0743***	0.1119***	0.0066	-0.1117***	95.08%
	(2.14)	(77.92)	(4.00)	(0.22)	(-7.34)	
Q7	0.0010***	1.0757***	0.1346***	0.1201***	-0.1255***	94.22%
	(3.03)	(69.34)	(4.27)	(3.56)	(-7.34)	
Q8	0.0008***	1.0931***	0.0950***	0.0290	-0.1224***	94.67%
	(2.65)	(74.29)	(3.18)	(0.91)	(-7.54)	
Q9	0.0008**	1.0724***	0.1641***	0.0922***	-0.1305***	93.90%
	(2.30)	(67.42)	(5.08)	(2.67)	(-7.44)	
Q10	0.0015***	1.1044***	0.1569***	0.2127***	-0.1751***	89.29%
	(2.93)	(47.71)	(3.34)	(4.23)	(-6.86)	
Q10-Q1	0.0006	-0.0231	-0.0826	-0.0046	0.0141	1.02%
	(1.05)	(-0.84)	(-1.48)	(-0.08)	(0.47)	

In Table B1 and B2 we show abnormal returns for the U.S market (S&P 500) when using company names as SVI measure. Table B1 and B2 show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 *for the model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week in Table B1 and from two weeks prior to investing in Table B2, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Number of observations: 512. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Table B3: Weekly abnormal return per portfolio for S&P 500 using ASVI for ticker symbols from the previous week

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	R^2*(%)*
Q1	0.0012**	1.2075***	0.2766***	-0.0294	-0.1680***	86.55%
	(2.10)	(43.95)	(4.96)	(-0.49)	(-5.55)	
Q2	0.0005	1.1291***	0.1911***	0.0368	-0.1598***	83.65%
	(0.85)	(38.96)	(3.25)	(0.58)	(-5.00)	
Q3	0.0013**	1.1347***	0.0646	0.1271**	-0.1791***	84.81%
	(2.18)	(40.19)	(1.13)	(2.07)	(-5.75)	
Q4	0.0000	1.0723***	0.1297**	0.0748	-0.0349	82.80%
	(-0.06)	(39.41)	(2.35)	(1.26)	(-1.16)	
Q5	0.0009*	1.1471***	0.0788	-0.1185**	-0.1120***	85.62%
	(1.53)	(44.61)	(1.51)	(-2.12)	(-3.95)	
Q6	0.0004	1.1297***	0.0950*	-0.0061	-0.1107***	85.92%
	(0.66)	(44.15)	(1.83)	(-0.11)	(-3.92)	
Q7	0.0007	1.0916***	0.2553***	0.0207	-0.0919***	82.62%
	(1.10)	(38.25)	(4.40)	(0.33)	(-2.92)	
Q8	0.0014***	1.0923***	0.1287**	0.0414	-0.1303***	86.35%
	(2.67)	(43.96)	(2.55)	(0.77)	(-4.76)	
Q9	0.0008	1.1089***	0.0262	0.1997***	-0.1442***	79.25%
	(1.07)	(33.22)	(0.39)	(2.75)	(-3.92)	
Q10	0.0019**	1.1900***	0.2135**	0.3156***	-0.3025***	69.73%
	(1.78)	(23.55)	(2.08)	(2.87)	(-5.43)	
Q10-Q1	0.0007	-0.0175	-0.0631	0.3450***	-0.1345**	5.14%
	(0.55)	(-0.30)	(-0.53)	(2.70)	(-2.07)	

Table B4: Weekly abnormal return for S&P 500 for quantiles sorted by ASVI for ticker symbols two weeks prior to investing

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*UMD*	R^2 *(%)*
Q1	0.0011**	1.1890***	0.2156***	-0.0272	-0.0776**	83.24%
	(1.76)	(39.97)	(3.57)	(-0.42)	(-2.37)	
Q2	0.0004	1.1581***	0.0617	0.0728	-0.1629***	83.25%
	(0.62)	(38.62)	(1.01)	(1.12)	(-4.93)	
Q3	0.0001	1.1508***	0.1323**	-0.0483	-0.1021***	85.08%
	(0.18)	(42.97)	(2.43)	(-0.83)	(-3.46)	
Q4	0.0007*	1.0949***	0.2279***	0.0350	-0.1002***	85.05%
	(1.31)	(41.69)	(4.27)	(0.61)	(-3.46)	
Q5	0.0004	1.0431***	0.2115***	0.0013	-0.0987***	84.77%
	(0.75)	(41.49)	(4.14)	(0.02)	(-3.56)	
Q6	0.0005	1.1466***	0.1430**	-0.0294	-0.1478***	84.08%
	(0.82)	(40.49)	(2.49)	(-0.48)	(-4.73)	
Q7	0.0012**	1.0868***	0.1396**	0.1224**	-0.1374***	84.11%
	(2.03)	(39.33)	(2.49)	(2.04)	(-4.51)	
Q8	0.0009*	1.1078***	0.0566	0.1588***	-0.0932***	85.13%
	(1.55)	(41.69)	(1.05)	(2.75)	(-3.18)	
Q9	0.0017***	1.1072***	0.1796***	0.1134*	-0.2006***	83.07%
	(2.65)	(36.91)	(2.95)	(1.74)	(-6.07)	
Q10	0.0022***	1.1713***	0.0751	0.2665***	-0.3353***	75.12%
	(2.37)	(27.05)	(0.85)	(2.83)	(-7.02)	
Q10-Q1	0.0011	-0.0176	-0.1406	0.2937**	-0.2577***	10.37%
	(0.93)	(-0.33)	(-1.28)	(2.50)	(-4.32)	

In Table B3 and B4 we show abnormal returns for the U.S market (S&P 500) when using ticker symbols as SVI measure. Table B3 and B4 show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 *for the model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week in Table B3 and from two weeks prior to investing in Table B4 , i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Number of observations: 512. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Table B5: Monthly abnormal return per portfolio for S&P Europe 350 using ASVI for company names from the previous week

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*WML*	*R^2(%)*
Q1	0.0069**	0.6801***	0.2191	0.1925	-0.1834**	67.44%
	(2.16)	(10.37)	(1.36)	(1.09)	(-2.08)	
Q2	0.0078***	0.6665***	0.2186	-0.0449	-0.2623***	64.01%
	(2.39)	(9.91)	(1.32)	(-0.25)	(-2.90)	
Q3	0.0056**	0.6819***	-0.0355	0.1220	-0.1284	64.67%
	(1.76)	(10.29)	(-0.22)	(0.68)	(-1.44)	
Q4	0.0082***	0.6419***	-0.0494	-0.0122	-0.2385***	62.61%
	(2.56)	(9.64)	(-0.30)	(-0.07)	(-2.66)	
Q5	0.0075***	0.6396***	-0.0862	0.0785	-0.2540***	64.81%
	(2.37)	(9.71)	(-0.53)	(0.44)	(-2.87)	
Q6	0.0097***	0.6486***	0.1824	0.0991	-0.3171***	65.85%
	(2.96)	(9.53)	(1.09)	(0.54)	(-3.46)	
Q7	0.0080***	0.6247***	-0.0292	0.3649**	-0.1456	64.81%
	(2.46)	(9.27)	(-0.18)	(2.01)	(-1.61)	
Q8	0.0062**	0.6557***	0.2517	0.0994	-0.2318***	66.98%
	(2.02)	(10.24)	(1.60)	(0.58)	(-2.69)	
Q9	0.0053**	0.6067***	0.3452**	0.3025*	-0.2004**	68.91%
	(1.80)	(9.96)	(2.30)	(1.85)	(-2.45)	
Q10	0.0051*	0.6317***	0.4630***	0.0983	-0.2535***	63.64%
	(1.55)	(9.22)	(2.74)	(0.53)	(-2.75)	
Q10-Q1	-0.0017	-0.0483	0.2440**	-0.0942	-0.0701	7.58%
	(-0.81)	(-1.10)	(2.25)	(-0.80)	(-1.18)	

Table B6: Monthly abnormal return per portfolio for S&P Europe 350 using ASVI for company names from two weeks prior to investing

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*WML*	*R^2(%)*
Q1	0.0081***	0.6513***	0.3098*	0.1838	-0.1777*	63.56%
	(2.43)	(9.47)	(1.83)	(0.99)	(-1.92)	
Q2	0.0089***	0.6610***	0.1443	0.0440	-0.3239***	68.65%
	(2.90)	(10.35)	(0.92)	(0.26)	(-3.77)	
Q3	0.0053*	0.6242***	0.1327	0.1406	-0.1417	56.51%
	(1.48)	(8.46)	(0.73)	(0.71)	(-1.43)	
Q4	0.0049*	0.6937***	0.1538	0.0053	-0.2130**	66.68%
	(1.56)	(10.70)	(0.96)	(0.03)	(-2.44)	
Q5	0.0078**	0.6601***	0.1020	0.0148	-0.2274**	62.10%
	(2.32)	(9.54)	(0.60)	(0.08)	(-2.44)	
Q6	0.0077**	0.6575***	0.2124	0.2452	-0.2680***	66.31%
	(2.30)	(9.46)	(1.24)	(1.31)	(-2.87)	
Q7	0.0052**	0.5887***	-0.0259	0.1917	-0.1853**	63.11%
	(1.70)	(9.22)	(-0.17)	(1.12)	(-2.16)	
Q8	0.0064**	0.6643***	0.1513	0.1869	-0.1554*	69.76%
	(2.21)	(11.10)	(1.03)	(1.16)	(-1.93)	
Q9	0.0073**	0.6246***	0.1449	0.2023	-0.2536***	66.88%
	(2.33)	(9.70)	(0.91)	(1.17)	(-2.93)	
Q10	0.0081***	0.6896***	0.2381	-0.0054	-0.2502***	68.07%
	(2.63)	(10.83)	(1.52)	(-0.03)	(-2.92)	
Q10-Q1	0.0000	0.0384	-0.0717	-0.1892	-0.0725	2.63%
	(0.00)	(0.80)	(-0.61)	(-1.47)	(-1.12)	

*In Table B5 and B6 we show abnormal returns for the European market (S&P Europe 350) when using company names as SVI measure. Table B5 and B6 show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week in Table B5 and from two weeks prior to investing in Table B6, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Number of observations: 117. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Table B7: Monthly abnormal return per portfolio for S&P Europe 350 using ASVI for ticker symbols from the previous week

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*WML*	*R^2(%)*
Q1	0.0069**	0.8777***	0.4068**	-0.1332	-0.4428***	71.70%
	(1.88)	(11.49)	(2.16)	(-0.65)	(-4.31)	
Q2	0.0052*	0.6522***	0.1944	0.2326	-0.1668	59.47%
	(1.42)	(8.63)	(1.04)	(1.14)	(-1.64)	
Q3	0.0067**	0.5165***	0.3955**	0.3079	-0.2230**	53.97%
	(1.83)	(6.82)	(2.12)	(1.51)	(-2.19)	
Q4	0.0044	0.6242***	-0.0249	0.2124	-0.0731	55.09%
	(1.20)	(8.30)	(-0.13)	(1.05)	(-0.72)	
Q5	0.0049*	0.5763***	-0.2356	0.1100	-0.1730*	54.31%
	(1.41)	(7.90)	(-1.31)	(0.56)	(-1.76)	
Q6	0.0035	0.7586***	0.2258	0.2578	-0.1859*	66.36%
	(0.97)	(10.08)	(1.22)	(1.27)	(-1.84)	
Q7	0.0066**	0.6879***	0.4106**	0.0838	-0.2546**	59.25%
	(1.70)	(8.61)	(2.09)	(0.39)	(-2.37)	
Q8	0.0082***	0.6257***	0.0065	0.1338	-0.3545***	66.36%
	(2.52)	(9.28)	(0.04)	(0.74)	(-3.91)	
Q9	0.0077**	0.6134***	0.2724	0.3228*	-0.2762***	65.79%
	(2.32)	(8.90)	(1.61)	(1.74)	(-2.98)	
Q10	0.0069*	0.6942***	0.7731***	-0.0233	-0.1812	45.44%
	(1.39)	(6.73)	(3.05)	(-0.08)	(-1.31)	
Q10-Q1	0.0000	-0.1835**	0.3663*	0.1100	0.2616**	16.17%
	(0.00)	(-2.23)	(1.81)	(0.50)	(2.36)	

Table B8: Monthly abnormal return per portfolio for S&P Europe 350 using ASVI for ticker symbols from two weeks prior to investing

	Alpha (α)	*Mkt-RF*	*SMB*	*HML*	*WML*	*R^2(%)*
Q1	0.0054	0.6599***	0.3689*	0.1300	-0.1048	52.78%
	(1.35)	(7.99)	(1.81)	(0.58)	(-0.94)	
Q2	0.0087**	0.6617***	0.5081**	0.1314	-0.4027***	59.65%
	(2.12)	(7.79)	(2.43)	(0.58)	(-3.53)	
Q3	0.0020	0.6862***	0.3012	0.0060	-0.2444**	60.86%
	(0.56)	(9.21)	(1.64)	(0.03)	(-2.44)	
Q4	0.0036	0.5683***	0.2086	0.2910	-0.2524***	61.06%
	(1.07)	(8.09)	(1.21)	(1.54)	(-2.67)	
Q5	0.0100**	0.6995***	-0.0529	0.0485	-0.0582	52.84%
	(2.52)	(8.54)	(-0.26)	(0.22)	(-0.53)	
Q6	0.0061	0.6715***	0.3166	0.3617*	-0.2176**	61.92%
	(1.59)	(8.50)	(1.63)	(1.70)	(-2.05)	
Q7	0.0039	0.7757***	0.1815	0.1968	-0.1248	69.03%
	(1.18)	(11.24)	(1.07)	(1.06)	(-1.35)	
Q8	0.0095**	0.5785***	0.0858	0.2809	-0.1001	50.34%
	(2.44)	(7.17)	(0.43)	(1.29)	(-0.92)	
Q9	0.0093**	0.6639***	0.3454*	0.1316	-0.4251***	61.33%
	(2.33)	(8.06)	(1.70)	(0.59)	(-3.84)	
Q10	0.0040	0.7943***	0.1181	-0.1693	-0.2938***	66.95%
	(1.15)	(11.04)	(0.67)	(-0.87)	(-3.04)	
Q10-Q1	-0.0014	0.1344	-0.2508	-0.2993	-0.1890*	7.04%
	(-0.36)	(1.65)	(-1.25)	(-1.37)	(-1.72)	

*In B7 and B8, we show abnormal returns for the European market (S&P Europe 350) when using company names as SVI measure. Table B7 and B8 show, from left to right, portfolios sorted on ASVI, the weekly abnormal return (α), Market-Risk factor (Mkt-RF), size factor (SMB), value factor (HML), momentum factor (UMD) and R^2 for the model. We have sorted the portfolios based on Abnormal Search Volume Index (ASVI) from the previous week in Table B7 and from two weeks prior to investing in Table B8, i.e. each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Number of observations: 117. T-statistics are shown in parentheses. * denotes significance at the 10% level, ** at the 5% level and *** at the 1% level.*

Exhibit C: Raw returns by market

Table C1: Weekly raw returns for S&P 500 using ASVI for company names over different time horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5
Q1	0.18%	0.27%	0.30%	0.32%	0.38%	0.36%
Q2	0.23%	0.28%	0.30%	0.31%	0.32%	0.33%
Q3	0.25%	0.30%	0.28%	0.33%	0.27%	0.32%
Q4	0.29%	0.26%	0.25%	0.29%	0.31%	0.28%
Q5	0.28%	0.31%	0.28%	0.24%	0.25%	0.29%
Q6	0.26%	0.25%	0.27%	0.32%	0.29%	0.27%
Q7	0.30%	0.29%	0.31%	0.31%	0.28%	0.33%
Q8	0.30%	0.33%	0.29%	0.31%	0.29%	0.29%
Q9	0.34%	0.28%	0.28%	0.24%	0.24%	0.23%
Q10	0.46%	0.31%	0.36%	0.26%	0.28%	0.26%
Q10-Q1	**0.28%**	**0.04%**	**0.06%**	**-0.06%**	**-0.11%**	**-0.10%**

In Table C1 we show weekly raw returns for different time-horizons between SVI and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we see the ASVI, while Week 5 contains the raw returns five weeks after we see the ASVI change and rebalance the portfolios. Thus, investing during week 0 is not feasible and is only shown for illustrative purposes.

Table C2: Weekly raw returns for S&P 500 using ASVI for ticker symbols over different time horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4	Week 5
Q1	0.11%	0.35%	0.34%	0.34%	0.39%	0.35%
Q2	0.17%	0.26%	0.26%	0.34%	0.21%	0.28%
Q3	0.17%	0.34%	0.23%	0.38%	0.30%	0.34%
Q4	0.18%	0.20%	0.28%	0.14%	0.32%	0.26%
Q5	0.23%	0.30%	0.24%	0.33%	0.29%	0.35%
Q6	0.32%	0.24%	0.26%	0.22%	0.31%	0.26%
Q7	0.41%	0.27%	0.33%	0.29%	0.28%	0.28%
Q8	0.37%	0.35%	0.30%	0.35%	0.35%	0.22%
Q9	0.38%	0.28%	0.38%	0.26%	0.18%	0.39%
Q10	0.72%	0.41%	0.44%	0.37%	0.41%	0.35%
Q10-Q1	**0.61%**	**0.07%**	**0.10%**	**0.03%**	**0.02%**	**0.00%**

In table C2 we show weekly raw returns for different time-horizons between SVI and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we see the ASVI, while Week 5 contains the raw returns four weeks after we see the ASVI change and rebalance the portfolios. Thus, investing during week 0 is not feasible and is only shown for illustrative purposes.

Table C3: Monthly raw returns for S&P Europe 350 using ASVI for company names over different time horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4
Q1	0.66%	1.00%	1.12%	1.11%	0.96%
Q2	0.98%	1.03%	1.09%	0.87%	1.31%
Q3	0.69%	0.92%	0.85%	0.82%	1.09%
Q4	0.75%	1.08%	0.80%	0.99%	1.01%
Q5	1.08%	0.99%	1.05%	0.96%	0.82%
Q6	0.94%	1.17%	1.01%	1.02%	1.21%
Q7	1.07%	1.11%	0.79%	1.05%	0.97%
Q8	1.03%	0.90%	0.97%	1.15%	0.97%
Q9	1.42%	0.80%	0.96%	0.84%	0.87%
Q10	1.09%	0.76%	1.09%	1.10%	1.19%
Q10-Q1	**0.43%**	**-0.24%**	**-0.03%**	**-0.01%**	**0.24%**

In table C3 we show weekly raw returns for different time-horizons between SVI and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we see the ASVI, while Week 5 contains the raw returns four weeks after we see the ASVI change and rebalance the portfolios. Thus, investing during week 0 is not feasible and is only shown for illustrative purposes.

Table C4: Monthly raw returns for S&P Europe 350 using ASVI for ticker symbols over different time horizons

Raw returns	Week 0	Week 1	Week 2	Week 3	Week 4
Q1	0.71%	0.91%	0.92%	0.27%	0.67%
Q2	0.96%	0.82%	1.01%	0.89%	1.38%
Q3	0.94%	0.86%	0.48%	0.97%	0.70%
Q4	0.71%	0.79%	0.57%	0.99%	0.75%
Q5	1.05%	0.75%	1.43%	0.72%	1.31%
Q6	0.78%	0.70%	0.89%	0.89%	1.02%
Q7	1.23%	0.91%	0.81%	0.79%	0.38%
Q8	0.97%	0.96%	1.28%	1.03%	0.82%
Q9	0.73%	0.97%	1.05%	1.28%	0.85%
Q10	0.70%	1.03%	0.70%	1.18%	1.37%
Q10-Q1	**-0.01%**	**0.12%**	**-0.22%**	**0.91%**	**0.69%**

In table C4 we show weekly raw returns for different time-horizons between SVI and returns, by portfolios sorted on Abnormal Search Volume Index (ASVI). Each week the portfolios are rebalanced into ten quantiles, where Q10 contains the firms with the highest ASVI and Q1 contains the firms with the lowest ASVI. The firms are held in the portfolio for the whole week and then resorted in the beginning of the following week based on new levels of ASVI. Week 0 contains the raw returns the same week as we see the ASVI, while Week 5 contains the raw returns four weeks after we see the ASVI change and rebalance the portfolios. Thus, investing during week 0 is not feasible and is only shown for illustrative purposes.