Aalto University
School of Business

Can you google the future? A study on the predictive power of Google Trends on company shares in the UK.

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Abstract

Google Trends was released in 2006. The service enables one to see the aggregated search volume for any defined term. After its release it has gradually been incorporated into academic research from various fields, most often as a proxy for global attention. The purpose of this study is to analyze how investor attention for a particular stock ticker, as measured by Internet search frequency, affects its future trade volume and share price in the UK market. The effect is analyzed separately for different time periods, market capitalization sizes and industries. In addition the paper looks at how searches originating globally and from the UK differ in their relation to company shares.

The data used in this study come from two different sources. Financial data is gathered via Datastream, including weekly share prices and trade volume. Search volume data is gathered manually from Google Trends for the company's London Stock Exchange ticker symbol. The final sample consists of 93 firms in the FTSE AllShare index from 2004 to 2011.

The results indicate that search volume does have predictive power over company shares. Firstly the study shows that searches for a company ticker have a direct and significant relation to current and future trade volume. Secondly, using a Fama-Macbeth cross-sectional regression it is proven that search volume predicts future abnormal returns at the 1%-significance level. A one-standard-deviation increase in abnormal search volume this week raises abnormal returns next week by 12.5 basis points, while resulting in price reversal in subsequent weeks. Furthermore the study finds that search volume data originating from the UK is not as good at predicting share price movement as global search volume.

Keywords Internet search, Investor attention, Google, FTSE, Ticker, Abnormal returns, Retail investor

Tekijä Leo Wuoristo

Otsikko Voiko Google ennustaa tulevaisuutta? Tutkimus yrityksen osakekurssin ennustamisesta Google Trendsin avulla Iso-Britannian markkinoilla..

Tutkinto Maisteri

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Tiivistelmä

Google julkaisi Trends-palvelun vuonna 2006. Palvelulla voi hakea minkä tahansa hakusanan hakumäärän kehityksen. Palvelua on käytetty eri tieteenalojen tutkimuksissa, usein mittarina maailmanlaajuiselle huomiolle. Tämän tutkimuksen tarkoitus on analysoida, miten sijoittajien huomio tiettyä osakekurssia kohtaan hakufrekvenssin kehityksellä mitattuna, vaikuttaa osakkeen tulevaisuuden vaihdantaan ja arvon kehitykseen Iso-Britannian markkinoilla. Vaikutusta tarkastellaan eri ajanjaksoilla, kokoluokissa sekä toimialoilla. Lisäksi tutkimuksessa vertaillaan, onko kansainvälisillä ja kansallisilla hakusanoilla eroa niiden kyvyssä ennustaa osakekurssin kehitystä.

Tutkimuksessa käytettävä aineisto on kerätty kahdesta eri lähteestä. Osakekurssiin liittyvät tiedot kuten viikoittainen osakekurssin hinta ja vaihdanta on haettu Datastream-palvelusta. Hakusana-frekvenssi on kerätty käsin Google Trends-palvelusta käyttämällä hakusanana yrityksen London Stock Exchange ticker -symbolia. Lopullinen otanta sisältää yhteensä 93 yritystä FTSE AllShare -indeksistä aikavälillä 2004–2011.

Tulokset osoittavat, että hakusanan hakutiheys ennustaa yrityksen osakekurssia. Tutkimus näyttää toteen, että yrityksen ticker-symboli haut ennustavat sen tulevaa vaihdantaa. Fama-Macbeth poikkileikkaava regressiota käyttämällä voidaan todeta, että hakusanat ennustavat osakekurssin kehitystä 1% -merkittävyysasteella. Yhden keskihajontayksikön lisäys poikkeavaan huomion tänä viikkona ennustaa 12.5 korkopisteen nousua poikkeavissa osakekurssin tuloissa ensi viikolla, mutta seuraavina viikkoina ilmiö kääntyy vastakkaissuuntaiseksi. Tutkimus myös osoittaa, että kansainväliset hakusanat ovat parempia kuin kansalliset ennustamaan osakekurssia.

Avainsanat Internet hakusanat, Sijoittajahuomio, Google, FTSE, Ticker, Poikkeavat tulot, Yksityissijoittajat

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1. INTRODUCTION

Research has always been limited by the quality of tools used for measuring, and once a new way of studying a subject is available it opens up a completely new depth of research. This phenomenon is clearly illustrated in modern medicine, starting with the development of the primitive microscope and leading to the current molecular level tools, each advance contributing to new understanding on how humans work from the discovery of bacteria all the way to genetics. The ability to measure in more detail, to gather richer data is at the forefront of most major new discoveries. The ability to measure the volume of users aggregated search queries (in a more approachable term; global attention) in real time is one such advance, and it has begun contributing to a vast array of different disciples.

In the area of finance there have been emerging studies based on users search queries since 2010. In the forefront of the research are Da, Engelberg and Gao (Later referenced as DEG) whose paper *In Search of Attention* is the first publication in Journal of Finance (October 2011) based on Internet search data. Due to the freshness of the study topic, there is a vast array of subjects to approach with users search data. This paper uses the DEG (2011) study as a reference paper and reflects on the findings of their study based on a different country, an expanded time horizon and modified search criteria. In addition this study expands the Google Trends tools used in previous research by analyzing how searches originating globally and from the UK differ.

1.1. BACKGROUND INFORMATION ON GOOGLE TRENDS

Google is a company that specializes in digital data facilitation; for general issues there is the basic Google service, for academia there is Google Scholar and for finance there is Google Finance. The company specializes in connecting people to the vast array of data in the Internet, which would otherwise be nearly inapproachable. Google searches are the most common way to navigate the Internet; in UK they contribute nearly 90% of all Internet searches (Table 1 and Figure 1). It should also be noted that Google is by far the most visited website in the world as shown by the internet traffic site Alexa Top Sites (www.alexa.com/topsites).

TABLE 1: GOOGLE UK MARKET PENETRATION

This table depicts the relative use, in percentages, of the biggest search engines in the UK market.

Rank	Search engine	Searches in October 2012	Searches in September 2012	Monthly change	Share of searches October 2011	Yearly change
1	Google	89,33 %	90,74 %	-1,41 %	91,02 %	-1,69 %
2	Microsoft	4,71 %	3,98 %	0,73 %	3,85 %	0,86 %
3	Yahoo!	3,33 %	2,83 %	0,50 %	2,79 %	0,54 %
4	Ask	2,13 %	2,00 %	0,13 %	1,81 %	0,32 %
5	Other	0,50 %	0,45 %	0,05 %	0,54 %	-0,04 %

Google makes the aggregate search frequency data, commonly referenced as *Search Volume Index* (SVI), available in their service Google Trends (www.google.com/trends). The SVI data is available for the public for any search term that has sufficient requests on a weekly frequency. The weekly SVI value is the number of searches for that term scaled by the time-series average. Data can be categorized based on the originating country of the request (and in the US on state level), a specific category (Apple in IT has different hits than Apple in Food), or a requested time frame. Data is available starting from 2004 and all the way to the previous week.

FIGURE 1: SEARCH VOLUME INDEX RESULTS FOR TOP-4 SEARCH ENGINES FROM 2004-2012

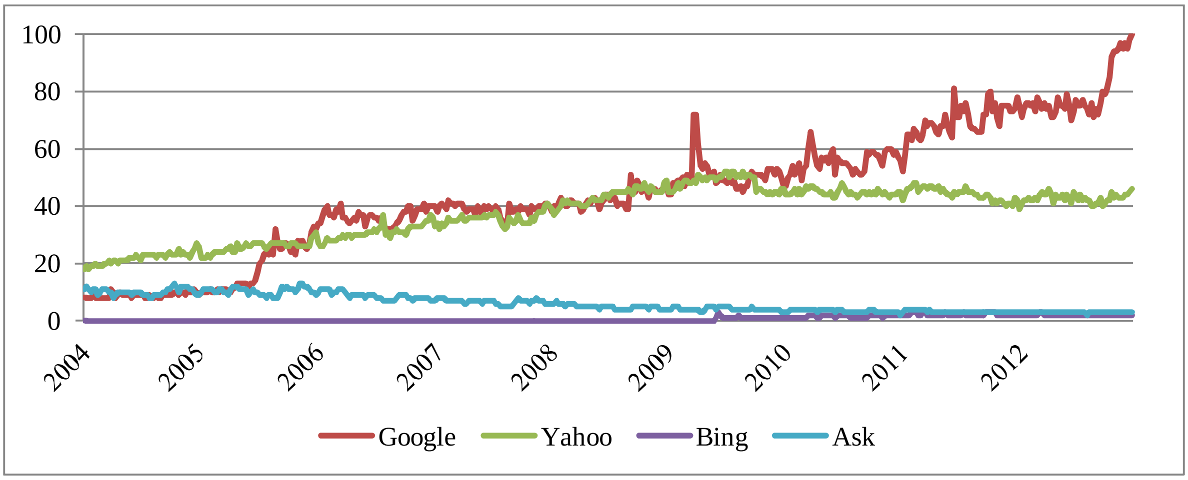
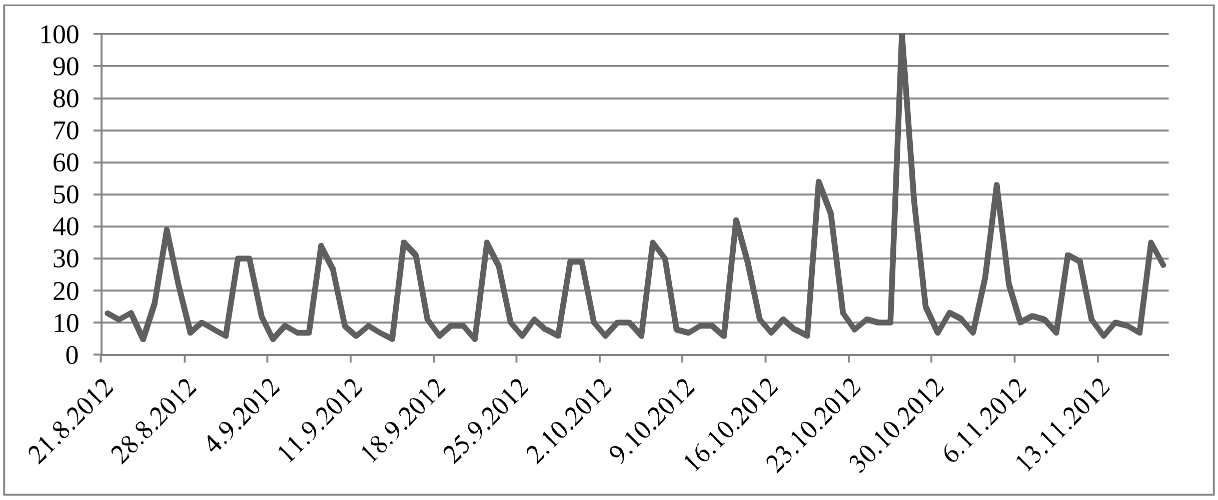


Figure 2 depicts the SVI for the word *lotto* originating from Finland for the past 90 days. Many conclusions can be made on how the Finnish population's attention around lotto behaves. SVI peaks are always on Saturday, which makes sense since that is the day that the lotto draw is done. People are either searching for the site to enter into the weekly draw or alternatively to view the results after the draw. There is also a little drift towards Sunday, which is explained most likely because it is another popular day to view Saturday's results. A small rise is evident on Wednesdays, which co-insides with the less popular Viking Lotto draw. Reassuringly the data shows that the size of the lotto prize directly correlates with the amount of attention it gets. The biggest prize in the history of Finland was at the end of October 2012 (12.2 mil. euro**)**. As we can see SVI seems to capture attention well.

FIGURE 2: SVI DATA FOR THE TERM "LOTTO" IN FINLAND



1.2. THEORETICAL BACKGROUND

Traditional asset pricing models make the assumption that information is instantaneously available to all stakeholders and reflected in the share price. However for this to hold, it requires all stakeholders to pay attention to the information once it is released. Kahneman (1973) argues that attention is a scarce cognitive resource and thus investors must choose what to pay attention to. Therefore investors must have a predefined choice set framed by their limited attention, from which they can make investment decisions.

There have been numerous studies on investor attention, based on different indirect proxies such as extreme returns, media attention and trading volume (Barber and Odean, 2008), price limits (Seasholes and Wu, 2007) or advertising expenses (Chemmanur and Yan, 2009). The results indicate that investors focus on attention-grabbing stocks and only then make the selection based on individual preferences. However these studies assume that a peak in one proxy would result in investor attention, which is not guaranteed. In the current digital age with all types of investors having easy access to global stock markets and company information, the questions of what to pay attention to becomes even more critical.

In 2011, the first study to use a *direct* measure of investor attention was published (Da, Engelberg and Gao). The paper uses Google's *Search Volume Index* (SVI) as a proxy for investor attention based on the assumption that searching on the Internet for a company reflects acute and direct interest. The study finds that weekly SVI, as a proxy for attention, correlates but is different from previous forms of attention measurement. The paper also shows that SVI captures the attention of retail investors, which is explained by institutional investors using more sophisticated tools to search for information, such as Reuters or Bloomberg terminals. One key contribution in the paper is to show that an increase in SVI for Russell 3000[1] stocks predicts higher stock prices in the next two weeks, which ends in price reversal within the year. The other main contribution to SVI research in the area of finance comes from Mondria and Wu (2011) who study the relation between local and non-local attention in the US market. They find that in situations of high information asymmetry (local attention is high without a similar increase in non-local attention) ticker SVI is a strong predictor of future share price movement, but however do not find a predictive effect when information asymmetry is low. This finding contradicts the results of Dao, Engelberg and Gao (2011), but can be explained by the fact that the study uses monthly data, instead of weekly.

1.3. RESEARCH PROBLEM AND PURPOSE

The predictive power of search queries has been a hot topic since 2009. The first significant result shows that Google search words have the power to predict influenza epidemics

[1] The Russell 3000 Index measures the performance of the largest 3000 U.S. companies representing approximately 98% of the investable U.S. equity market. It is completely reconstituted annually to ensure new and growing equities are reflected.

(Ginbsberg et al, 2009) and since then many areas of academia have started to analyze what this new tool could offer their research. There has been little academic exploration on SVI and its relation to finance for now. However that is likely to change due to the significant findings of the Da, Engelberg and Gao study and the constant improvements to the analytics tool. The aim of this paper is to answer two questions;

1. Does SVI capture investor attention in the UK market?
2. Does SVI predict the stock market in the UK market?

The motivation behind this paper is to validate the findings of Da, Engelberg and Gao (2011) by replicating a part of their study with companies listed in FTSE AllShare index. Furthermore this study expands the time-horizon by four years to capture the increase in digital consumption and effects of the global recession. In comparison to the DEG (2011) paper this study uses different variables to examine the relation between SVI and share price; such as how different industries affect the predictive power of SVI. Furthermore this paper uses a new function of Google Trends to compare how searches originating from the UK and globally differ.

1.4. CONTRIBUTION

This is the first study, to my knowledge, to examine the relation between SVI and the UK market. The aim of this paper is to examine the link between SVI and company shares while contributing to the expanding literature based on search volume data. The key reference study that this paper follows is the paper by DEG (2011) and aims to expand on their results by analyzing the same effect but using a different market, time horizon, additional variables and new Google Trend functions.

The results show that the same effect presented by DEG (2011) is evident with UK data although it is different. Firstly the study shows that there is a relation between trade volume in the UK and a company’s London Stock Exchange ticker search frequency. The study finds that increase in investor attention to a company ticker this week does have a positive effect on share price the following week. The results are significant at the 1%-level and show that a one-standard-deviation increase in ASVI (Abnormal Search Volume) today leads to a 12.5 basis point rise among FTSE AllShare stocks next week. Price reversal effects are evident but not as strong as in the DEG (2011) study. Surprisingly the study also finds that searches originating globally are better at predicting share price movement than searches originating from the UK.

The results are validated by multiple robustness checks. Firstly the data is sorted by industry, since it could be assumed that industries with high consumer visibility would interest retail investors more. Secondly the data is sorted by market capitalization to see how size might affect results. Thirdly the data is examined in different time frames to see if the outcome could be affected by the recession or alternatively the increase of Internet adoption in households. However the sample data size is not sufficiently large to provide significant results on the robustness analysis.

This study contributes to the increasing amount of search volume based research by examining for the first time the relation of ticker SVI and the stock market in UK. The study shows that searches originating from the UK and searches globally are not identical and provide different results towards the predictability of share movement. The main contribution of this study is to show that search volume does capture investor attention, is related to company shares and can be used to predict future stock market movements.

1.5. LIMITATIONS OF THE STUDY

The dependence on Google’s SVI data creates multiple limitations on the accuracy and scope of the study. Firstly the data is accessible on a weekly level, which means that currently there is no effective way of delving deeper into the data to see how attention shifts on a daily basis. Google only shares the relative increase or decrease based on the average search volume for a specific time period, and omits the numerical values of search transactions. Furthermore, there needs to be a sufficient amount of searches for Google to publish SVI’s which means that the lesser known companies will not produce any SVI data. Another limitation is that many companies have noisy tickers, such as British American Tobacco’s ticker BATS, which cannot be used to measure SVI since it would also pick up on searches for the nocturnal animals.

Another key limitation is that this study does not incorporate the use of any web crawling software and collects SVI data by hand. The benefit of this method is gaining a better understanding of the data and its relation to what is measured, but the cost is that the sample size must be limited due to the time-consuming process of collecting the data.

The rest of the thesis is organized as follows. Section 2 presents the most important literature on studies based on SVI data as well as studies based on the effect of attention. Section 3 presents the research hypotheses, Section 4 the data and Section 5 the methods used. The results are presented in Section 6, and Section 7 concludes.

2. LITERATURE REVIEW

This chapter reviews the literature relevant to this study. The chapter is divided into two sections. Section 1 examines the different studies made based on the Search Volume Index, firstly looking at the area as a whole and then focusing in more detail to research around finance. Section 2 discusses the literature concerning investor attention and its effect on company performance.

2.1. PREVIOUS LITERATURE INVOLVING SVI

The following two subsections discuss the literature pertaining to Search Volume Index research. The first subsection describes literature from different field of academia, while the second subsection focuses on the applications of SVI in finance.

2.1.1. SVI LITERATURE IN GENERAL

Google released their Trends product to the public on May 10th in 2006 and it has gone through multiple iterations during the past six years. From an academic perspective, the significant date was the first release of Google Insight (which was integrated into basic Trends in 2012) in 2008, which enabled statistical analysis due to CSV importing and major improvements in data reliability.

The literature on search volume has been relatively abundant when taking into consideration that the data has been available and usable since 2008. However the concept of using Internet behavior to predict real world changes has been present for a longer time, which partly explains the quick incorporation of Trends for research purposes. Johnson et al. (2004) test if monitoring Internet web page visits to sites that give information on influenza can predict flu peaks. The results were moderately strong and no clear connection could be established at the time, however it paved the road for future studies. A year later, Cooper et al. (2005) describe using Internet search volume for cancer-related topics. The first literature on the significant predictive power of SVI comes from the medical field as well. Ginsberg et al. (2009) found that that search data for 45 terms associated to influenza predict flu outbreaks one to two weeks before Center for Disease Control and Prevention (CDC) reports. This study is often referred to as the verification that Google Trends has predictive power and can be used as the basis for academic research. One example of its significance is the fact that Google has incorporated Ginsberg's flu predictions as a part of the base Google Trends product (http://www.google.org/flutrends/).

Google's Chief Economist Hal Varian has suggested that Google search data has the potential to describe interest in a variety of economic activities in real time. In their study Choi and Varian (2009) show that search data can predict home sales, automotive sales and tourism. In the example of tourism, they make the assumption that Google is used for travel planning and therefore an increase in destination related queries should indicate future trips to that destination. The study looks at queries for the term *Hong Kong* from nine different locations and compares it to the Hong Kong Tourism Board's monthly visitor statistics, which includes the traveler's place of origin. The study shows that there is a strong correlation (with the exclusion of Japan) between the two parameters.

In their research Goel et al. (2010) examine how search query volume forecasts the opening weekend of box-office revenue for a feature film, first-month sales of video games and the rank of songs on the Billboard Hot 100 chart. They conclude that SVI provides a useful guide to predicting sales days, even weeks into the future. The predictability power varies between different forms of media, being strongest in movies and weakest in music. In addition to consumers purchasing trends, SVI has been used to measure their political actions. Lui et al. (2011) find that SVI is a poor indicator of voting results in the US during the 2008 and 2010 congressional elections, due to the fact that voter's attention towards a candidate does not directly indicate an interest to vote for that candidate, it is just as likely that they are following up on negative news. However general voting activity could be measured using SVI.

One of the key areas where SVI research has been applied is economics, one indication being that the Central Bank of England has taken it to use as an economic indicator. The first paper known to suggest using web search data to forecast economic statistics was by Ettredge (2005), which examined the U.S unemployment rate. Multiple studies have shown this suggestion to be valid, since a strong link between job search related queries (e.g. unemployment office, jobs, resume) are shown to be linked to unemployment payments (Baker and Fradkin, 2011) and unemployment (Askitas and Zimmerman, 2010; Choi and

Varian, 2011). Guzman (2011) showed that SVI can also predict inflation, by evaluating it against 36 survey measures and showing that *Google Inflation Search Index* (GISI) has the lowest forecast error of all the inflation expectation indicators tested. SVI has been used to evaluate the economic sentiment by creating an index consisting of the SVI for a subset of negative words (e.g. recession or bankruptcy). The study shows that an increase in the index leads to return reversals, extreme volatility and mutual fund flow; from equity heavy funds to bond funds (Da, Engelberg, Gao, (b) 2010). An alternative take on the same link is shown by Dzielinksi (2012) who uses the word *economic* as a proxy for economic uncertainty. His assumption is based on the hypotheses that a higher level of uncertainty increases the demand for information, which in modern society would be visible in Internet search data and queries related to the word economic. Another substitute word that has been suggested to indicate US investor confidence is the search for the term *gold*, since investors shift their attention from equity to alternative investment opportunities in economic downturns (The Economist, 2011).

2.1.2. SVI LITERATURE AND FINANCE

In the area of finance SVI has been used primarily as an indicator of attention (Da, Engelberg and Gao, 2011; Modria and Wu, 2011; Modria et al., 2010). The reference study that this paper is based on is by DEG, released in Journal of Finance in October 2011. Their study examines how an increase in investor attention (as measured by SVI) relates to previous attention measures, such as media attention, extreme returns and investor sentiment in Russell 3000 stocks during 2004-2008. They find that SVI leads all other attention proxies and thus captures investor attention in a more timely fashion, which is rational because there can be no extreme returns without pre-existing investor attention and investors most likely pay attention to stocks well ahead of scheduled news events (such as earnings announcements).

The study also evaluates whose attention SVI is capturing, by cross-referencing retail orders found in monthly Dash-5 orders with SVI. To ensure that retail attention is captured the origin of the order is used as an additional proxy. The assumption is that a market center, such as Madoff Investment Securities, that pays for order flow is used by retail investors, whereas more informed investors often go to the New York Stock Exchange for NYSE stocks which does not pay for order flow and is a typical venue of the last resort. The study shows that SVI is more correlated with Madoff orders and suggests that SVI captures the attention of individual investors as opposed to institutions. The reasoning behind this is that institutions have more sophisticated tools to gather information than Google, such as Reuters or Bloomberg terminals.

The third result found in the study is that SVI is strongly correlated with the price pressure hypothesis of Barber and Odean (2008). The study shows that a one-standard-deviation increase in ASVI (Abnormal SVI) leads to a significant positive price change of 18.7 basis points in Russell 3000 stocks (calculated using the methods presented by Daniel et al (1997), later referenced DGTW). The positive price pressure is only present in the smaller half of the stock sample and is stronger in retail investor driven Dash-5 trading volume than total trading volume. Price reversal is evident after the third week, and the positive change is completely reversed in under one year. DEG (2011) conclude that ASVI seems to be the only measure of attention that predicts both the initial price increase and subsequent long-run price reversal. The study also looks at how SVI towards a company's main product (PSVI) affects share price, but find it to have no significant predictive power. Finally the paper evaluates the attention-induced price pressure hypotheses and SVI with IPO stock returns. It is confirmed that there are significant changes in SVI around the IPO week, starting with an upwards trend two to three weeks prior to the offering and resulting in a spike on the release week and reverting to pre-IPO levels in subsequent weeks. The study shows that ASVI strongly predicts first-day IPO returns and that successful IPO's with high ASVI underperform successful IPO's with lower ASVI, since they are not subject to price pressure.

An alternative perspective on the same principals has been offered by Mondria and Wu (Mondria et al. 2010; Mondria and Wu 2011; 2012). They also base their hypotheses on Barber and Odean (2008) and the price pressure hypotheses and use the direct attention measure of SVI as a proxy for stocks from S&P 500. However they look at how local's and non-local's attention differs by using a Google Trends feature for search query location filters, more specifically different states in the US. In the first study (2010) they evaluate the effect of home bias by analyzing search queries and show strong support for the anomaly, since local investors disproportionately search for local companies. They further expand their analysis (2011) to show that when local attention rises without a similar increase in non-local attention (high information asymmetry) it indicates that some internal local news has entered the market. The effect is strongest in remote areas, due to the fact that information spreads slower from there. The study shows that information asymmetry estimated by using SVI to measure local attention versus non-local significantly predicts abnormal stock returns. Interestingly they do not manage to replicate the findings of DEG (2011) in their data and find no significant relation with non-local SVI and abnormal returns. This is most likely due to the fact that the study is based on monthly data, and DEG (2011) showed strong price reversal starting on the third week. In their latest study (2012) they test SVI attention behavior and its effect on local and foreign (non-US) investments. They show that attention increase in foreign stocks results in US sales of foreign stocks, which is in conflict with the general hypotheses and results of DEG (2011) who showed that attention indicates price pressure and is related to buying stocks. Mondria and Wu (2012) show in their study that US investors increased attention to foreign stocks does not result in similar actions as increase towards local stocks. In foreign stocks bad and surprising news gets a disproportionately higher SVI as opposed to good or familiar news.

Substituting investor attention with information demand, Vlastikis and Markellos (2012) study how search query volume predicts stock market volatility. Their study is based on the assumption that investors demand more information as their level of risk aversion increases. The study focuses on the 30 largest stocks traded in NYSE and shows that information supply (as measured by Reuters news for a company) and information demand (as measured by company SVI) do not behave in a similar manner. Information demand is driven by historical volatility and trading volume, whereas supply is highly periodic and systematic. The study also shows that using the expected risk premium for the S&P 500 as a proxy for time-varying risk aversion confirms for the first time the hypotheses that information demand increases with the level of risk aversion in the market.

TABLE 2: AN OVERVIEW OF FINANCE LITERATURE USING SVI

This table depicts the key research that uses search volume index data as a basis for empirical study.

Researchers	Name of study	Journal	Year	Data	Range and frequency	Motivation	SVI proxy	Results
Da, Engelberg and Gao	The sum of All FEARS	Working paper	2010	Russell 3000	2004-2008, Weekly	Measuring market sentiment via search volume.	Queries related to household concerns (bankruptcy, recession, credit card debt)	Increase in SVI proxy is associated with low returns today and predict high returns tomorrow. They also predict excess volatility and daily mutual fund flow.
	Internet Search and Momentum	Working paper	2010	Russell 3000	2004-2008, Weekly	The momentum effect strength in relation to search volume.	Company ticker signs	Companies with high SVI have stronger momentum effect.
	In search of Fundamentals	Working paper	2010	Russell 3000	2004-2008, Weekly	Revenue surprises and earnings announcement surprises in relation to search volume.	The name of a firms most popular product	Product search volume has strong predictability for returns around earnings announcements.
	In search of Attention	Journal of Finance	2011	Russell 3000	2004-2008, Weekly	Measuring investor attention via search volume.	Company ticker signs, product name and company name	Ticker search volume predicts future share price movements and price reversal.
Mondria, Wu and Zhang	The determinants of international investment and attention allocation	Journal of International Economics	2010	S&P 500	2004-2009, Monthly	Measuring home bias via search volume.	Local attention versus non-local attention on company ticker	Local companies are searched significantly more locally than non-locally.
Mondria and Wu	Asymmetric Attention and Stock Returns	Chicago Meetings Papers	2011	S&P 500	2004-2009, Monthly	The effect of asymmetric information, as measured by search volume, on share price.	Local attention versus non-local attention on company ticker	Local asymmetric attention predicts stock increase.
	Familiarity and Surprises in International Financial Markets	Working paper	2012	S&P 500	2006-2010, Monthly	Measuring how attention to local stocks and foreign stocks differ using search volume.	Foreign equity exchange index ticker	US Investor attention is different from foreign stocks. Attention peaks during foreign market downturns.
Vlastakis and Markellos	Information Demand and Stock Market Volatility	Journal of Banking and Finance	2012	30 largest stocks in NYSE	2004-2009, Weekly	Measure information demand via search volume for company and compare it to information supply as measured by Reuters news articles.	Company name	Information demand does not correspond with the supply.
Dimpfl and Jank	Can Internet search queries help predict stock market volatility	Working Paper	2012	Dow Jones index	2006-2011, Daily	Measure investor confidence via search volume.	Dow Jones index name	Search queries Granger cause index volatility.

2.2. PREVIOUS LITERATURE INVOLVING ATTENTION

Traditional asset pricing models assume that information is instantaneously calculated into stock prices when it arrives. These models assume that investors have undivided attention to all assets and their corresponding information streams. However that is understandably not the case since attention is a scarce cognitive resource (Kahneman, 1973) and due to cognitive limitations investors must choose what they pay attention to; an increase in cognitive resources to one task requires a substitution from another task. The limitations of the perfect-market model and costs to information seeking are at the core of Merton's (1987) paper on capital market equilibrium with incomplete information.

Research on investor's limited attention and its implications has been plentiful. Hirshleifer and Teoh (2003) take the assumption of limited attention and look at how the quality of company disclosures can affect the attention of investors. Since investors have a limited amount of time on hand, they must make choices on how much information they gather on a company. The hypothesis is that due to limited attention company disclosures that clearly state information are absorbed more readily and the more information an investor can gather the less risky that investment will seem.

Corwin and Coughenour (2008) follow how limited attention affects specialists and their NYSE portfolio's liquidity by monitoring specialists during their work. They find that in periods of increased activity the specialists allocate effort toward their most active stocks, while the other securities are subject to less attention resulting in a lack of liquidity. The negative effects of running out of liquidity are frequent price improvements and increased transaction costs. The behavioral implications of limited attention for investors are also discussed in the paper of Peng and Xiong (2006). They show that with limited attention investors start focusing on category-level information (such as market and sector information), as opposed to firm-specific information. The study also shows that limited attention promotes overconfidence, since decisions need to be based more on investor sentiment than actual company specifics.

Since it has been relatively well established in literature that investors have limited cognitive abilities which result in limited attention, the logical follow-up question is; what grabs their attention? In his paper Odean (1999) proposes that investors manage the problem of choosing between thousands of possible stocks by limiting their search to stocks that have recently caught their attention. In other words attention forms the subset of options for which investment decisions can be made, and those investment decisions can vary per individual, such as following a contrarian approach or being a momentum investor (Barber and Odean, 2008). The availability heuristic is one of the most common explanations for attention allocation for uninformed investors.

There are multiple *indirect* proxies of investor attention in financial literature such as extreme returns, media attention and trading volume (Barber and Odean, 2008). It is logical to assume that when investors are pushed information it is more likely that they will notice it. An example of this is when a company exhibits overly positive or negative returns, since it becomes increasingly likely that the investor will pay attention to it than on an average performance day. Price limits (Seasholes and Wu, 2007) and advertising expenses (Chemmanur and Yan, 2009) are also used as proxies for investor attention. Price limits are based on the disposition effect and the idea that when a new high (or low) price for a stock is reached, it gathers relatively more attention. Advertising expenses work as a proxy by assuming that the more money a company puts into advertising the more familiar it is with investors and the more familiar it is results in higher attention, since investors are more likely to follow firms they know compared to unfamiliar ones.

Barber and Odean (2008) test and confirm their hypothesis that individual investors are net buyers of attention grabbing stocks, and therefore an increase in individual attention results in temporary price pressure. The logic behind this assumption is that when investors are buying stocks, they have to choose from a large set of available options. However when selling they can only sell stocks that they own (with the rational assumption that individual investors do not short their position). Therefore shocks to retail attention should lead on average to net buying from uninformed traders. This finding is the basis for hypothesis two (H2) in this study.

3. HYPOTHESES AND DATA IMPLICATIONS

This chapter presents the hypotheses between Search Volume Index and company shares. The hypotheses are based on the theories relating to investor attention and the empirical findings of previous research. The first Section discusses the differences between the data in this paper and that of the DEG (2011) and what implication the differences may have on the results. The second Section presents the hypothesis of the study. All in all there are five hypotheses discussed below.

3.1. THE DIFFERENCES IN DATA TO THE REFERENCE STUDY

There are two major differences in data between this paper and that of DEG (2011) that could affect the results.

TABLE 3: INTERNET ADOPTION RATES: UK VS. US

This table depicts the absolute and relative amount of Internet users in the UK and the US between years 2000 to 2010.

The UK

Year	Population	Users	% Pop.
2000	58,789,194	15,400,000	26.2 %
2005	59,889,407	35,807,929	59.8 %
2007	60,363,602	38,512,837	63.8 %
2009	61,113,205	48,755,000	79.8 %
2010	62,348,477	51,442,100	82.5 %

The US

Year	Population	Users	% Pop.
2000	281,421,906	124,000,000	44.1 %
2005	299,093,237	203,824,428	68.1 %
2007	301,967,681	212,080,135	70.2 %
2009	307,212,123	227,719,000	74.1 %
2010	310,232,863	239,893,600	77.3 %

Firstly the market is different since the DEG (2011) paper is based on US stocks and the Russell 3000 index, whereas this paper is based on UK stocks and the FTSE AllShare. There is no cause to assume that the results would be different depending on the country, but it is possible. The UK market has higher Internet adoption rates per capita than the US (Table 3), and has higher usage of Google (89%, Table 1) for searching than the US (66.1%, Experian

Hitwise report, 2012). Both of these facts support the hypothesis that retail investors would use the Internet and more specifically Google to gather information on the companies they are interested in, even more so than in the reference study.

There are no studies that contribute to understanding the behavioral differences between retail investors in the UK and US. Therefore the only possibility is to rely on the data available and make assumptions based on the data. However it should be noted that it is possible that retail investor behavior differs from country to country. For instance it is possible that US investors are more active traders than UK investors, and might therefore search for the ticker more frequently to inspect company information or alternatively UK investors could rely more on other sources of company information such as blogs or newspapers.

It should be noted that the US population (approximately 311 Million) is five times bigger than that of the UK (approximately 63 Million), which means that there will be less search volume in total in the UK. This might have an effect on the smaller companies being excluded from the study due to not having enough search queries to show up on Google Trends. Furthermore it should be noted that in the DEG (2011) study the smaller firms where significantly affected by SVI and in bigger firms the effect was not visible.

Another market based issue is the total amount of retail investors. Although the UK market is an investment hub, it is strongly dominated by big institutional investors. Although there should be no major difference in retail investors per capita, once again the sheer volume of the US market means that there are more retail investors in total. As DEG (2011) show in their study, SVI captures the attention of retail investors and therefore it could be that the results are weaker due to less retail investors in the UK as a whole compared to the reference study.

Another difference in the US and UK markets that can affect the data is the type of companies that are in the indexes. In Section 4.1.1 the stock market data is described in detail. One difference that is pointed out is that there are proportionately more consumer related stocks in the Russell 3000 index which are recognizable to investors. Following the findings of Barber and Odean (2009) retail investors are much more inclined to invest in companies they are familiar with. Since many companies in the FTSE AllShare are in industries that are not visible to consumers, there is a risk that retail investor attention will be low. It is likely that in general the FTSE AllShare index does not garner as much retail interest attention as the major US companies featured in the Russell 3000 index. On the other hand there is less participant fluctuation in the FTSE AllShare index (median age 18yrs and average age 23yrs) as opposed to the Russell 3000 index, so the study benefits from longer and more sequential firm-week observations.

The other difference between this study and that of the reference paper is the time frame. The DEG (2011) study consists of data up to June 2008, whereas this study has data up to December 2011. The subprime financial crisis of 2007-2008 that involved the bailout of banks, the bankruptcy of Lehman Brothers and subsequently led to the current global recession should most likely be visible in the data, since investor confidence sank and money shifted away from equity. The decrease in retail investor participation in equity markets should be visible in data, starting from 2008 to the end of 2009 (Figure 3). However the extended period also enables more robust analysis of the SVI effect on share prices, since the time-frame of this study is nearly two times longer than that of DEG (2011).

FIGURE 3: FTSE ALLSHARE INDEX PERFORMANCE 2004-2011

3.2. THE HYPOTHESES OF THE STUDY

The first hypothesis concerns SVI and trade volume in the UK market. Based on the findings of DEG (2011) it is reasonable to assume that also in the UK market SVI for a company ticker is a valid proxy for retail investor attention. If that is the case then an influx of attention toward a company ticker should have an effect on trade volume, since retail investors are more likely to trade stock they are aware of as opposed to unknown stocks. The assumption is supported both by the availability heuristic (Kahneman and Tversky, 1982) and price pressure theory (Barber and Odean, 2008).

Hypothesis 1 (H1): An increase in a company's tickers Search Volume Index affects the change in trade volume for that company.

If a link between retail investor attention, as measured by SVI, and stock trade volume can be established, then the next step is to understand what type of effect there is. There is no cause to assume that behavior between retail investors in the US and the UK would be significantly different. Based on the price pressure hypothesis of retail investors presented by Barber and Odean (2008), and previously shown to be accurate in the US market by DEG (2011), this paper states the hypothesis that with an increase in company ticker SVI, the company share price is more likely to rise than decrease. However the effect should completely reverse during a period of one year, as in the study of DEG (2011).

Hypothesis 2 (H2): An increase in Search Volume Index for a company's ticker has a positive effect in the short-run for that company's share price, but will reverse in under one year.

The third hypothesis presented in this paper is that the effect of price pressure due to individual buying activity should be more present in smaller stocks. This assumption is based on the idea that small stocks are subject to larger price impact, as was shown in the study of DEG (2011).

Hypothesis 3 (H3): The effect of the price pressure from retail investor attention is stronger in small companies compared to large companies.

The fourth hypothesis is based on the finding of Chemmanur and Yan (2009) that retail investors are more likely to purchase stocks they are familiar with. To test this we look at the industries that have high consumer recognizability (e.g. consumer goods) and propose that such companies will be more influenced by the retail attention measured by SVI.

Hypothesis 4 (H4): Companies with high consumer recognizability are more affected by retail investor attention than companies that are not visible to consumers.

The fifth and final hypothesis has to do with the way in which SVI is gathered. There is no way to escape a certain amount of noise in the data, since for most three to five letter combinations there is a corresponding meaning. The meaning can be a medical abbreviation, computer virus, camera model or simply a word written wrong. By narrowing down the market from global search words to UK based search words it can be assumed that the possibilities for different meanings should be narrowed down. This would mean that the results for UK stock tickers should be stronger in the UK SVIs than in global SVIs, since there is less chance for noise. The effect of home bias also supports this hypothesis, since it claims that investors are more inclined to invest in local stocks. Therefore we can assume that locals will be looking more at local stocks, however the study of Tesar and Werner (1995) shows that UK has the least amount of home bias compared to Germany, Canada, US and Japan.

Hypothesis 5 (H5): The SVI results from UK are better predictors for UK company share price than the SVI results gathered globally.

However it should be noted that for hypothesis five (H5) there is also a good chance that global SVI results are more indicative due to the bigger amount of search volume in general. If the ticker is searched for multiple times more around the world than in the UK, then the global SVI can also withstand multiple amounts of noise and still be as valid.

TABLE 4: A LIST OF THE HYPOTHESES

This table depicts the five hypotheses of the study and related previous research.

No.	Statement	Previous studies
H1	An increase in a company's tickers Search Volume Index affects the change in trade volume for that company.	Da, Engelberg and Gao (2011)
H2	An increase in Search Volume Index for a company's ticker has a positive effect in the short-run for that company's share price, but will reverse in under one year.	Da, Engelberg and Gao (2011)
H3	The effect of the price pressure from retail investor attention is stronger in small companies compared to large companies.	Da, Engelberg and Gao (2011)
H4	Companies with high consumer recognizability are more affected by retail investor attention than companies that are not visible to consumers.	None
H5	The SVI results from UK are better predictors for UK company share price than the SVI results gathered globally. .	None

4. DATA AND SAMPLE

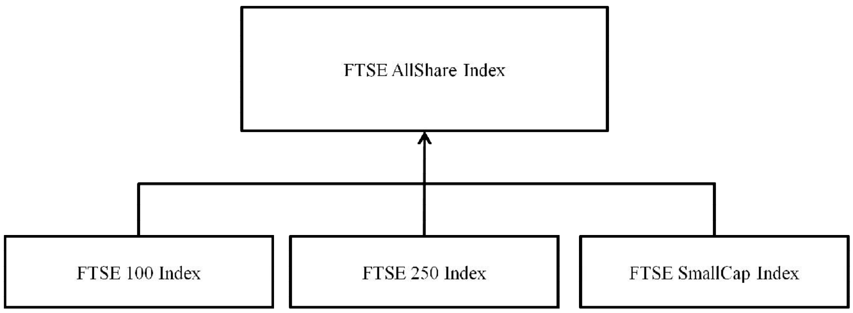
In this chapter, the data and sample of this study are presented. Section 1 describes the data used in the study, firstly describing the stock market data gathered from DataStream and then describing data gathered via Google Trends. Section 2 charts the sample formation process and describes the final sample.

4.1. DATA

The data for this paper comes from two sources. The first subsection describes the stock market data derived from DataStream and the following subsection the Search Volume Index data collected manually from Google Trends.

4.1.1. STOCK MARKET DATA

FIGURE 4: FTSE ALLSHARE COMPOSITION



The study uses data from companies in the FTSE AllShare Index. The index is the aggregation of FTSE 100 Index, FTSE 250 Index and FTSE SmallCap Index (Figure 4). The index aims to represent at least 98% of the full capital value of all UK companies that qualify for inclusion. As of November 2012 the index constituted of 601 companies or funds. As in the reference study by DEG (2011) all stocks participating in the index during the sampling period of January 2004 to December 2011 are included (total 57) to eliminate survivorship bias and the impact of index addition and deletion. In accordance with the DEG (2011) study all stock-week observations with a market price below two pounds (approximately the three dollars used in DEG (2011)) are omitted to alleviate market microstructure-related issues.

TABLE 5: VARIABLE DEFINITIONS

This table defines the main variables used in the study. Variables are derived from two sources: Datastream and Google Trends.

Variable	Definition
Variables from Datastream	
Ret (R)	Weekly stock return
Abnormal Ret (AR)	Weekly excess returns (Return – (Index return * Company Beta))
Trade volume (TV)	Weekly trading amount measured in shares traded per day
Turnover (T)	Weekly turnover (Trade volume/Shares outstanding)
Abnormal Trade Amount (AT)	Weekly excess volume, calculated from turnover (Traded volume/Shares outstanding)
Market cap (MC)	Weekly market capitalization
Shares outstanding (SO)	Weekly amount of shares outstanding
Industry code (I)	Monthly ICB industry codes as given by DataStream
Variables from Google Trends	
SVI UK (SVI_{uk})	Aggregate weekly search frequency from Google Trends from IP-addresses in UK based on stock ticker
SVI Global (SVI_{Glo})	Global weekly aggregate search frequency from Google Trends based on stock ticker
ASVI (ASVI)	The log of SVI during the week minus the log median SVI during previous 8 weeks as in DEG (2011)

The data gathered for the sample on a weekly level are the stocks trade volume, stock price, market cap and shares outstanding from January 2004 to December 2011. As the utilized methods require data from previous years, data is also collected from 2002-2004, as well as FTSE AllShare index value from 2002-2011. In addition we gather on a monthly level the industry code of the company. All data is collected using Datastream (Table 5).

TABLE 6: FTSE ALLSHARE INDUSTRY COMPOSITION

This table depicts the absolute and relative composition of industries in the FTSE AllShare index. Weigh in size is defined as the market cap of the industry compared to the total market cap of FTSE AllShare index.

Industry	No of Companies	Weight in size (%)
Oil and Gas	26	16,99
Basic Materials	36	10,1
Industrials	109	9,06
Consumer Goods	35	13,7
Health Care	13	7,27
Consumer Services	85	9,47
Telecommunications	8	6,08
Utilities	7	3,99
Financials	257	21,88
Technology	25	1,47
Totals	**601**	**100**

The FTSE AllShare index is comprised dominantly by financial companies (257/601) and industrial companies totaling over half of the constituents (Table 6) although when measured by weight in size the 26 oil and gas companies constitute nearly 17% of the FTSE AllShare size. It is good to note that the index is dominated by a handful of companies, since the top 10 companies constitute over 38% of the total market size (Table 7). In comparison to the Russell 3000 index [2]used in the DEG (2011) study there are similarities, since both indexes are dominated by financial companies. However one important difference is a clearly stronger presence of consumer visible companies with a higher recognizability to the average investor in the Russell index, such as Apple, Amazon and Microsoft. Consumer goods and consumer services constitute only a fifth of companies in FTSE AllShare with 120 out of 601.

[2] A comprehensive description of the Russell 3000 constituents, market cap and fund performance can be found online at: http://www.russell.com/Indexes/data/fact_sheets/us/Russell_3000_Index.asp

TABLE 7: THE LARGEST COMPANIES OF FTSE ALLSHARE

This table depicts the largest constituents of FTSE AllShare and their country, industry, market cap and weight related to the whole FTSE AllShare index.

Constituent	Country	Industry group	Mcap (GBPm)	Weight (%)
HSBC	UK	Banks	112,034	6,47
BP	UK	Oil and Gas Producers	84,388	4,87
Vodafone Group	UK	Mobile Telecommunications	83,028	4,79
Royal Dutch Shell A	UK	Oil and Gas Producers	78,541	4,53
GlaxoSmithKline	UK	Pharmaceuticals & Biotechnology	69,574	4,02
British American Tobacco	UK	Tobacco	59,663	3,44
Royal Dutch Shell B	UK	Oil and Gas Producers	57,985	3,35
Diageo	UK	Beverages	44,606	2,57
BHP Billiton	UK	Mining	41,935	2,42
Rio Tinto	UK	Mining	38,733	2,24
Totals			**670,487**	**38,7**

There are two main reasons for selecting FTSE AllShare index in the UK market. One is the inclusion of the SmallCap index. Since the DEG (2011) study showed that retail investor attention and price pressure hypothesis is most dominant in small cap firms it would be good to include as many as possible to test the effect in the UK market. The second reason is that FTSE AllShare is the most comprehensive of the used indexes in UK. It is important to have a big sample size since there will be many omissions due to the lack of data. However including all companies in London Stock Exchange would require huge efforts on gathering SVI data and as can be seen in the following chapter, smaller firms do not get sufficient amount of search volume to produce SVI data.

4.1.2. SVI DATA

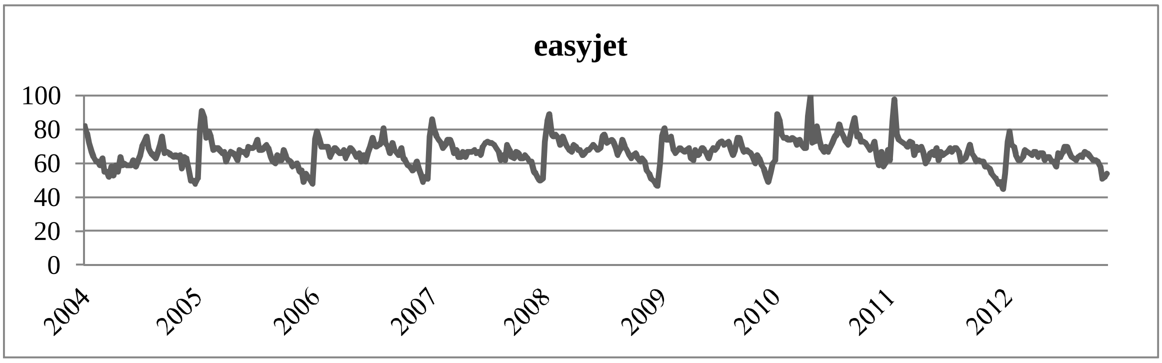
SVI data is collected from Google Trends by manually entering the company ticker used in London Stock Exchange to the search field and downloading the CSV file. Data is available from 2004 onwards, however due to privacy and anonymity requirements Google will only publish information if there is a sufficient amount of queries available. This means that no SVI information will be available for companies that have few search queries. There are numerous choices in how the data should be collected via Google Trends.

The first question is what identifier should be used to capture investor attention for a given company. DEG (2011) show that ticker symbols capture the attention of retail investors and argue that using a generic company name is partial to too much noise, since the cause of a search word can be related to anything.

As a concrete example the company EasyJet (Ticker: EZJ) has a very high and periodical SVI for the company name, but the ticker behavior is very different. This is due to the fact that most people are searching for the word EasyJet when they are interested in travelling. The seasonality of travel is quite clear in the data, since peaks occur during holidays (Figure 5). Ticker SVI does not show any seasonality and seems to be driven by other factors that travelling. There is a peak on the start of 2011 which coincides with a Reuters news article about EasyJet buying 15 new Airbus planes (http://www.reuters.com/finance/stocks/EZJ.L/) . It can be assumed that the ticker is searched for when the user is interested in financials. The SVI data shows that the ticker term is searched for only from the UK, whereas the company name is searched for also from other neighboring European countries enforcing the assumption that there are different motivations driving the searches.

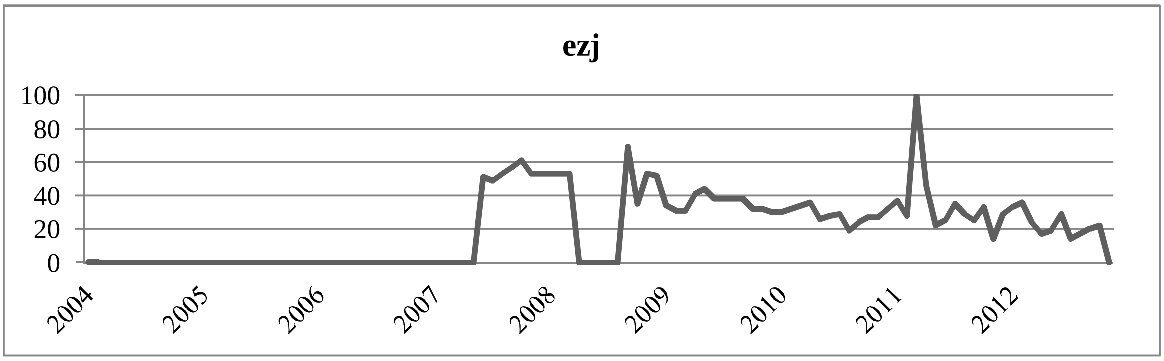
When collecting the ticker SVI the likelihood that the results capture investor attention should increase significantly. This paper aims to follow the DEG (2011) study and therefore uses tickers as the main identifier.

FIGURE 5: A COMPARISON OF SVI RESULTS FOR COMPANY NAME AND TICKER



Top regions for Easyjet

United Kingdom	100
Switzerland	87
Portugal	55
Italy	55
France	48
Spain	36
Greece	27
Ireland	20
Morocco	19
Slovenia	16



Top regions for EZJ

United Kingdom	100

The second empirical question concerns the area where the search queries originate from. Google Trends allows the user to filter country specific searches or global searches. The DEG (2011) study does not comment on this part, most likely since when their study was first started, this option was not yet available. Since the study is interested in finding the link between investor's attention and company shares, the global results should be used. If the study was focused on only UK investors, then it would be sound to use a country filter.

While conducting the analysis it became evident that much of the noise can be eradicated from the study by focusing on country specific queries. For instance the ticker for the online gambling company 888 Holdings is H888, however the same code is used for an Asian mobile phone model. Therefore when searching globally for H888, the SVI results include people interested in investing in the UK and buying mobile phones in Asia. It can also be assumed that there is some form of home bias effect in retail investors and thus there would be more UK company related searches in the UK (Werner and Tesar, 1995). By using the country filter the probability that the study captures the right type of attention should increase (H5). In this study both the global and the UK data are collected so that both results can be evaluated.

There are additional functions that Google Trends offers that could be used in the study. Google Trends has an option to use industry and category filters, so it would be possible to search for firms using their industry as a filter. This might reduce noise, but since Google does not clearly define the process, the risk of an internal filtering error affecting the sample is not taken in this study. Google Trends does allow users to download daily data, but only if the time frame is 90 days or less. Considering the period of eight years used in this study it would require more than 100 independent queries to collect the data for one company. As mentioned in the opening paragraph this study collects manually all data from Google Trends, which is informative since the quality of data can be viewed as it is being collected. However many studies, such as DEG (2011), use web crawling technology to automate the collecting process. The bigger the required sample size and especially if daily values are collected, web crawlers become increasingly useful.

It should be acknowledged that due to efficiency reasons Google does not calculate all search queries in the SVI results, but only a sample of the total. However in the study of DEG (2011) it was shown that there is very little deviation in the results after multiple test runs of collecting the same sample.

4.2. SAMPLE

The following Section describes the sample. The first subsection charts the sample definition process and how the final sample size has been formed. The second subsection delves deeper into the final sample characteristics and goes through the factors that might have an effect on the results of the study.

4.2.1. SAMPLE SIZE AND DEFINITION PROCESS

The total sample size is 658 companies from which 601 are listed in 2012 and 57 are from previous years. To eliminate survivorship bias and the impact of index addition and deletion, all stocks that have been listed during 2004-2012 are included in the total.

In this study there have been four processes that have determined the sample size. Firstly, the FTSE AllShare index includes both equity and investment trusts. All investment trusts have been omitted from the sample due to two reasons. Firstly, it is important to replicate the DEG (2011) study as closely as possible to ensure that the results are comparable. Since the investment trusts are solely available in the UK and not used in the DEG (2011) sample, they are omitted. The second reason is that investment trusts most likely do not attract retail investor attention similarly as equity, although both securities are traded in the London Stock Exchange. Investment trust funds are reallocated based on the fund manager's disposition, and are therefore fundamentally different types of securities.

The second process that defines the sample size is the omission of noisy tickers from the sample. Noisy tickers are symbols that can have alternative meanings, such as British American Tobacco's ticker BATS or Glencore's ticker GLEN. These tickers cannot be used to evaluate investor attention due to the fact that they would more likely be capturing the alternative meaning of the word.

There have been two steps to complete this process. Firstly the list has been cleaned from the obvious noisy tickers, such as words or names. Secondly during the SVI search process the results of each ticker are reviewed. Google Trends informs of related words associated with the search term with each search (Table 8). There are two different values given for any search. One is the ”Top searches” which lists the most common word combinations associated with the term. The scale is from zero to 100. A score of 100 does not mean that the term is always used, but simply that it is used the most. The other value is "Rising searches" that highlights the terms that have had significant growth in the given time period with respect to the preceding period. The value of "Breakout" is assigned to terms that have experienced a growth of over 5000% during the period.

The results of the related words can often uncover noise that would otherwise go unnoticed. For instance the ticker for industrial company Keller is KLR, and while searching for the SVI of the ticker it is apparent that there is strong seasonality and peaks, which indicates that there might be noise in the data. When looking at the related terms it shows that KLR is also a model of Kawasaki motorbikes and since the relation with KLR and motorbikes is very strong the ticker must be omitted from the study. The rule that is followed in this study is that if there is a clear alternate definition that has a value of 100, the ticker is omitted. In other cases the results are accepted. In the best scenario the results show that related terms include words such as share, price, news or info which gives a strong indication that the search query is related to the company. However this happens very rarely during the collection process. It must be noted that there will be a certain amount of noise in a search volume based study, but by monitoring the results the risk can be minimized.

TABLE 8: AN EXAMPLE OF A NOISY TICKER

This table depicts the top search and rising search values associated with the term klr.

Top searches for klr	
klr 650	100
kawasaki klr	90
kawasaki klr 650	50
klr 250	45
klr 600	25
klr for sale	20
kawasaki klr 250	20
kawasaki klr 600	10
Rising searches for klr	
kawasaki klr 250	Breakout
kawasaki klr 600	Breakout
klr 250	Breakout
klr 600	Breakout
klr for sale	Breakout
klr 650	180 %
kawasaki klr 650	40 %

The third process that defines the sample size is the omission of the companies that do not have sufficient data to conduct the analysis. There are two sources that can result in insufficient data. Firstly, if the company is recently listed in FTSE AllShare (listing occurs after 2010) there might not be enough data. Secondly, if there are too few search queries for the company, Google Trends will not produce SVI data, which means that the lesser known companies will need to be omitted from the study. The minimum requirement for sufficient data in both cases is one year of sequential data.

The fourth and final process is to review all the SVI data collected from Google Trends to confirm that the data is on a weekly level. When listing results Google Trends does not indicate if the results are on a weekly basis or a monthly basis. When there are relatively few search queries the data is delivered at a monthly level. This timeframe however does not suite the study, since the interest is in capturing investor attention close to the event. For instance in the DEG (2011) study price pressure was strong for one week and price reversal started on the third week after high SVI. To compare results with the DEG (2011) study, weekly data is mandatory. Table 9 depicts the initial sample size, the omission per process and the final sample size.

TABLE 9: FINAL SAMPLE SIZE

This table depicts the final sample size and the different processes that have defined it.

Data	Volume
FTSE AllShare constituents 2012	601
Additional constituents during 2004-2012	57
Total constituents	**658**
Investments trusts	178
Noisy tickers - pre search	63
Noisy tickers - post search	102
Insufficient company data	59
Insufficient SVI data	98
Only monthly SVI	65
Final sample size	**93**

4.2.2. Sample characteristics

This Section describes the sample characteristics from different perspectives. The first thing to note is that the sample size has shrunk during the data collection process to 15% of its original size. To understand the results of the study it is valuable to understand what has been omitted. In Table 10 we see that the emphasis of industries has shifted remarkably.

TABLE 10: INDUSTRY REPRESENTATION IN THE FINAL SAMPLE

This table depicts the number of constituents per industry in the final sample and in FTSE AllShare.

Industry	No. in Sample	No. in FTSE AllShare	Proportion (%)
Consumer Services	18	85	21 %
Financials	17	257	7 %
Industrials	15	109	14 %
Basic Materials	11	36	31 %
Consumer Goods	10	35	29 %
Technology	8	25	32 %
Health Care	6	13	46 %
Oil & Gas	3	26	12 %
Telecommunications	3	8	38 %
Utilities	2	7	29 %
Total	**93**	**601**	**15 %**

The relative amount of companies from consumer related industries such as consumer services and consumer goods has increased whereas only 7% of the financial industry companies are present in the final sample. It is evident from the data that consumer-visible companies dominate the sample, while less known companies did not receive enough searches to receive SVI values. This result is interesting in itself since it hints at the findings of DEG (2011) that SVI captures retail investor attention, and retail investors are more inclined to search for stock they are familiar with.

The descriptive statistics are presented in Table 11. The table shows that share price for the time frame has been relatively low. The mean return is 0.1% for the whole period for FTSE AllShare index, and 0.2% for the sample. We also note that standard deviation for the sample is much higher than for the AllShare index which is in line with the higher return rate. The important thing to note is the possible effect of the recession and participant withdrawal from the equity market, due to the low investment outlooks. If equity is not interesting for the retail investor, their attention might divert to something else, as has been shown by analyzing the link between economic downturn and the rising search frequency for gold (The Economist, 2011).

The other interesting finding is the behavior of the two different SVI values. The SVI collected from the UK market has a standard deviation value that is twice as large as that of SVI global. This is rational due to the fact that there are fewer participants that generate search volume in the UK. The global value carries with it more general noise, which makes singular attention peaks more difficult to attain. The same effect can be noticed from the mean values of the SVI's. The UK SVI mean is nearly 30% smaller than the global value, meaning that the general attention is lower. It can be that the lower amount of noise enables the more volatile UK SVI to have stronger predictive power, but it is also possible that the results might suffer due to insufficient data.

TABLE 11: DESCRIPTIVE STATISTICS OF THE SAMPLE DATA

This table presents descriptive statistics for the sample data consisting of 93 firms from the FTSE AllShare index. The data consists of weekly observations from January 2004 to December 2011.

	FTSE Index Ret.	Excess Ret.	Raw Ret.	ASVI_UK	SVI_UK (log)	ASVI_Global	SVI_Global (log)	Abnormal Vol.	Vol. (Log)	Market Cap. (Log)
Mean	0,0010	0,0020	0,0020	0,0000	1,1490	-0,0007	1,6162	1,0088	3,2307	9,2582
Standard deviation	0,0285	0,0607	0,0603	0,0876	0,7024	0,0659	0,3115	0,1376	0,9483	0,8023
Minimum	-0,2019	-0,6416	-0,6513	-1,3299	0,0000	-0,4624	0,0000	0,0000	0,0000	7,1060
Maximum	0,1611	1,2244	1,2518	1,1871	2,0000	0,6576	2,0000	5,1779	8,4651	11,2444
Total observations	417	35154	35154	35154	35154	35154	35154	35154	35154	35154

5. METHODS

The study replicates the methodology used by Da, Engelberg and Gao (2011) with certain omissions and additions. The following Section is divided into two parts. The first subsection discusses the process to calculate all required parameters and create a cross-correlation matrix. The second subsection presents the methods used to create the regression analysis.

5.1. CROSS-CORRELATION MATRIX AND REQUIRED PARAMETERS

There are three abnormal values that need to be derived from the collected data: abnormal stock returns, abnormal trading volume and abnormal search volume.

Weekly abnormal stock returns (AR_{it}) are calculated by comparing expected returns ($E(R_{it})$) to realized returns (R_{it}) for week t and company i. Expected returns are calculated from the benchmark index (R_{mt}) using a company specific beta (β_{it}). In this case expected returns are calculated by taking the weekly performance of the FTSE AllShare index and multiplying it with a company-specific risk measure beta. The beta is derived from a company's historical data by regressing the past two years of company stock returns to the index returns and is re-calculated every two years to ensure validity,

$$AR_{it} = R_{it} - E(R_{it}),$$

$$E(R_{it}) = R_{mt}\beta_{it},$$

In the study by DEG (2011) they use Daniel et al. (1997, later on abbreviated DGTW) to calculate abnormal returns. However the method is not used in this study due to the small heterogeneous sample size which is less affected by momentum, industry and size factors and also since the DGTW is designed to normalize returns for the US market.

Weekly abnormal volume is calculated from changes in turnover (T), which is the relation of traded volume (TV) to outstanding shares (OS). This is used to normalize data since stocks have different amounts of shares and naturally a company with many shares should have more trade volume than a company with fewer shares. To calculate abnormal volume (AV) we use a similar method to ASVI calculation (applied from DEG (2011)) where we compare the current turnover to the median of the past eight weeks to find peaks of abnormal volume,

$$T_{it} = \left(\frac{TV_{it}}{OS_{it}}\right),$$

$$AV_{it} = log\, T_{it} - log\, Med(T_{it} - 1, \ldots, T_{it} - 8)\_\,,$$

It is important to find the abnormal attention peaks in the search volume (SVI) data. To do this we calculate a new variable called abnormal search volume (ASVI) which is the log of SVI during the week minus the log median SVI during the previous eight weeks, as was done in the study by DEG (2011). This enables to find the important attention peaks that are tested against the company's own share price and trade volume. The formula below depicts how the ASVI is derived,

$$ASVI_{it} = log\, SVI_{it} - log\, Med(SVI_{it} - 1, \ldots, SVI_{it} - 8)\_\,,$$

In situations where there is no available data for share price, trade volume or search volume that firm-week is omitted from the study.

5.2. Regression methods and hypotheses testing

TABLE 12: METHODS USED TO TEST HYPOTHESES

This table describes the different methods used to test the five hypotheses of the study.

	Simple OLS regression
H1	The relation between SVI and Trade volume
	Fama-Macbeth (1973) Cross-sectional regression
H2	The relation between SVI and Share price
H5	The relation of SVI (UK) and SVI (Global) as predictors
	Robustness checks
H3	The effect of firm size on results
H4	The effect of industry on results

The first hypothesis (H1) that is tested is the relation between the trade volume and SVI. This can be analyzed using Simple OLS regression where the trade volume (TV) is used as the depended variable and independent variables are SVI (SVI), stock returns (R) and log market cap (MC). The method used is described below,

$$TV_i = \beta_0 + \beta_{1i} SV_i + \beta_{2i} R_i + \beta_{3i} MC_i + \varepsilon_i,$$

For the second and fifth hypotheses (H2, H5) this study uses a cross-sectional Fama-Macbeth (1973) regression as in the reference study by DEG (2011). The method provides direct estimates on the marginal effect of the explanatory variable and is therefore a good way to analyze ASVI's predictive power on share prices. The Fama-Macbeth model is a robust way of analyzing large quantities of panel data, meaning multiple assets across time. The methodology provides standard errors that are corrected for cross-sectional correlation.

The cross-sectional regression is a two stage process that starts by first calculating the effect of the ASVI on each asset separately. Once the regression is run for all the companies we have an understanding of how the selected explanatory variables tested affect the company's returns. The second stage regressions explain the premium rewarded for each exposure. In the second regression all asset returns for a fixed time period are regressed using the estimates from the first regression. In this study there are five different time horizons for which the dependent variable future (t+1) abnormal returns (calculated in basis points) are regressed; the first four weeks and then the remaining year (weeks 5-52).

The following regression is run to calculate the weekly estimates for the coefficients,

$$AR_{it} = \gamma_{ot} + \sum_{k=1}^{K} \gamma_{kt} X_{kit} + \varepsilon_{it} \qquad t = 1,2,\dots,T,$$

where AR_{it} is the abnormal return on stock *i* in week *t*. T is the total number of weeks in the sample. X_{kit} are the potential explanatory variables in cross-sectional expected returns. As a base set of these determinants of the cross-sections of returns the study uses the abnormal search volume (ASVI), trade volume (TV) and market cap (MC). In practice the regression is run for 93 companies weekly for duration of 8 years (January 2004 to December 2011). The results are reported in the following Section.

For the third and fourth hypothesis (H3, H4) the study conducts a robustness analysis where the data is sorted based on market cap and industry to see how the effects change based on different cross-sections of the data.

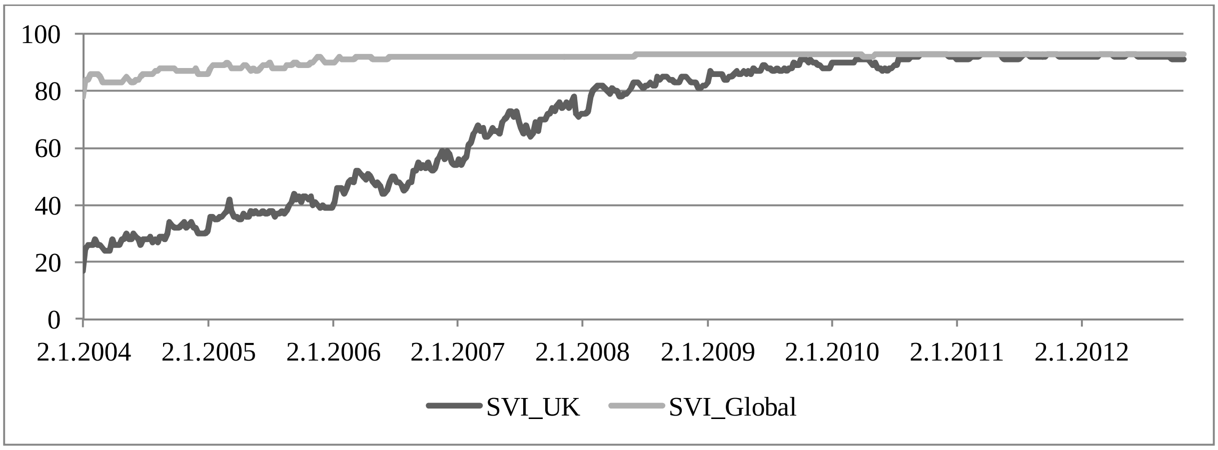
6. RESULTS

The following Section presents the results of the study. The first Section discusses general findings of the study, which are based on the sample statistics. The second Section analyzes the correlations between different parameters to understand the relation between them. The third Section presents the regression results and robustness checks.

6.1. GENERAL FINDINGS FROM DATA CHARACTERISTICS

This study is based on a novel dataset and it is important to analyze the quality and structure of it to understand what is being measured. The first thing that is looked at is the amount of data received via Google Trends. Although all data in our sample is on a weekly level, there is still the option that a certain ticker has not been searched for during that specific week (or more correctly a sufficient volume of searches has not been met and therefore SVI remains zero for that week). Figure 6 depicts how many tickers from the sample size of 93 produced a search frequency value over zero.

FIGURE 6: NUMBER OF COMPANIES WITH SEARCH VOLUME OVER ZERO FROM 2004-2012

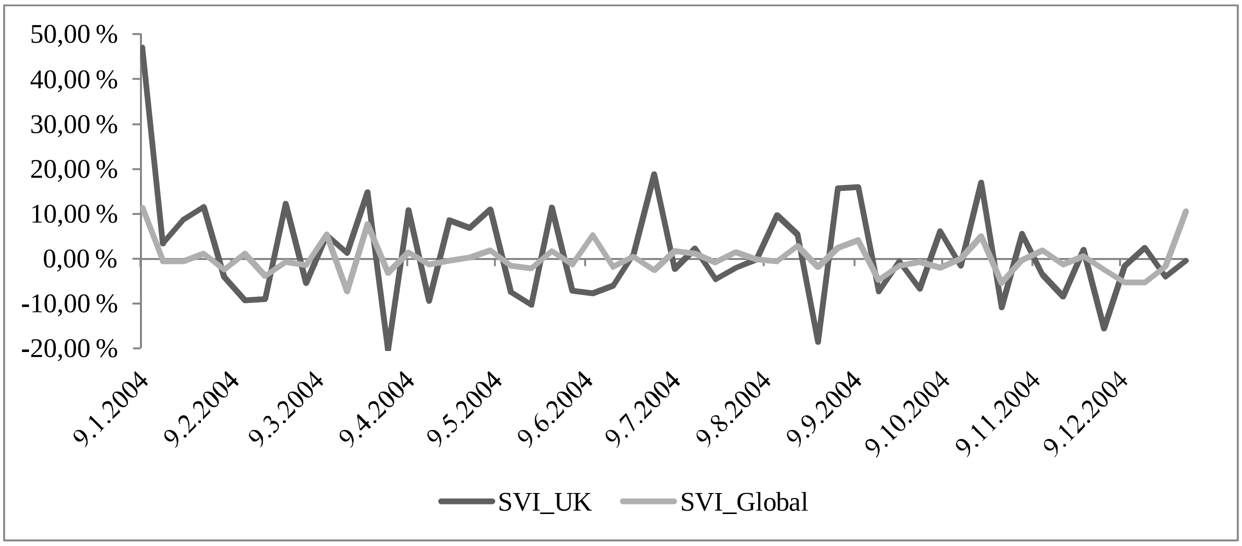


As Figure 6 depicts, the amount of results over zero for global SVI is relatively stable and always over 80. This outcome is understandable since there are globally many more Internet users than locally, and therefore for any given search there will always be more hits globally than locally. For results collected from the UK the trend is clearly rising with January 2004 having a total of 14 ticker searches and by the end of 2008 the amount is leveling over 80.

This is most likely due to two factors. The first is the availability of the Internet to retail consumers. In 2005 Internet penetration rate for households in the UK was under 50% (Report from UK Office for National Statistics) whereas in 2010 it was over 80% (Table 3). The other reason is the rising popularity of Google as a search engine. In 2004 there was a variety of competitors, but now in the UK Google accounts for nearly 90% of all searches (Table 1 and Figure 1). This finding is important since it indicates that the UK SVI could have more predictive power as searches increase for retail investor's post 2007. The implications are that data will not be as significant in the first years of the study.

Comparing the SVI data for UK and global markets offers valuable insight on the higher standard deviation of the UK results in relation to the global ones (Figure 7).

FIGURE 7: THE RELATIVE CO-MOVEMENT OF THE SVI AVERAGES FOR YEAR 2004



One logical theory for why global data has less variance is that the global results average out due to more noise. Looking at the actual data, global results have a high volume of searches every week, whereas in the UK there are many weeks when the SVI is zero. Since there are less searches in the UK than in the world the weight of single searches is much bigger in the UK. Another interesting aspect to note in the data is that the sharp attention peaks of the UK SVI do not seem to have a clear effect on the global SVI data. In the regression testing the log SVI will be used to minimize skewness and kurtosis.

The final general test is to look at the co-movements of share prices, and the SVI to see if any indicative predictive power can be found (Figure 8).

FIGURE 8: THE RELATIVE CO-MOVEMENT OF THE SVI AND SHARE PRICE AVERAGES FOR YEAR 2008

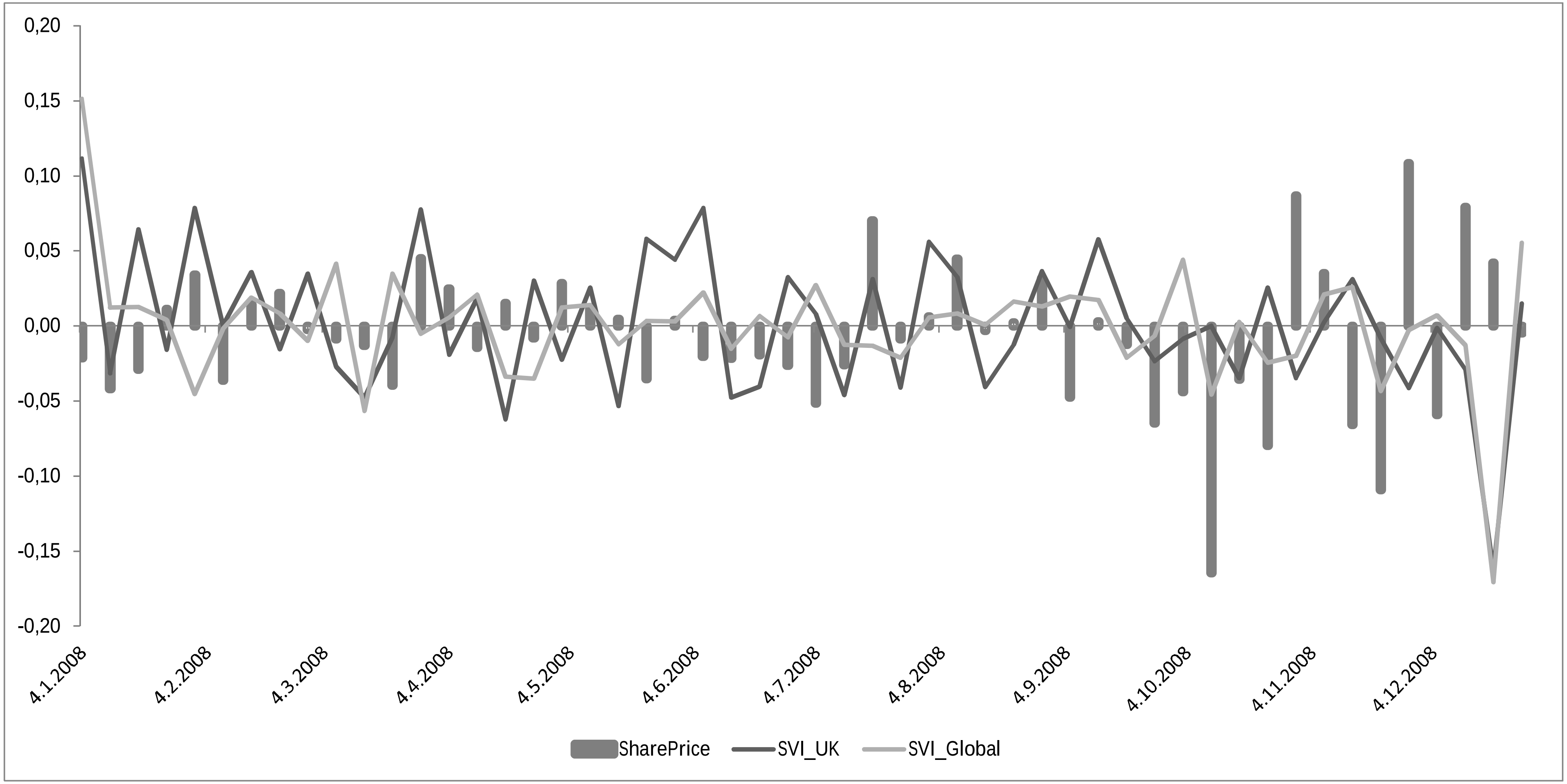


Figure 8 depicts the co-movement of the UK SVI, SVI Global and the share price, by calculating the relative change per week for all companies in the sample in 2008. Two distinct findings can be made from Figure 8.

Firstly, there seems to be very little co-movement between the SVI values and the share price, especially the extreme peaks seem unrelated. The huge share price dips in the end of 2008, or the subsequent bounce backs do not seem to create similar reactions in the SVI. The same effect can be viewed in the SVI data, where especially UK SVI seems to have erratic peaks through-out the year.

The other finding is that the ticker SVI is very high in the beginning of January and low at the end December. Upon analyzing the data we find this result repeats itself year after year. If ticker SVI indicates investor attention, one assumption that could be made is that in December the retail investors are occupied with the holiday season and their attention toward stock tickers decreases. In January the interest raises once again after the holiday. This could point to the fact that the SVI captures retail investor’s attention due to the seasonality of the results, whereas institutional investors do not react to seasonality as much. However, if the SVI does not capture investor attention, then the effect most likely attributes to the general search volume seasonality.

6.2. CROSS-CORRELATION MATRIX

The values of the correlation between sample variables are presented in Table 13. The values are calculated on same-week basis and there is no lag in the data. There are multiple points to note from the matrix. Firstly the correlation between returns and other sample variables seems to be quite low. This is in line with the findings of the DEG (2011) paper that finds the correlation between abnormal return and turnover to be 0,059 and 0,035 respectively, which is explained by the fact that there are multiple factors contributing to share price movement.

The second finding in the correlation matrix is on the relation between SVI UK and SVI Global. The correlation value of 0,319 indicates some relation between the two variables, which means that there is a link between searches happening in the UK and around the world. However the explanation for this value can be contributed to at least three effects.

The first explanation is the general seasonality of the searches. There are clear high and low periods for search activity, such as the start of the year as a high peak and the end of the year as a low peak. Therefore it can be that the relation simply has to do with general search volume happening at the same time, not that investors in the UK and around the world are analyzing the same company. The second explanation is that there is a noise value that is being picked up by the correlation. While gathering the SVI data, it becomes evident how much noise simple ticker symbols can generate. Therefore it can be that Internet users are searching for something unrelated to the company, but it still gets captured in the SVI value. The third explanation is that there is a link between the investors in UK and around the world searching for company information and it is being captured. In any case the key finding is that the UK and global SVI's are capturing different attention for the most part and therefore it is valuable that this study analyzes both separately.

The third finding is the relation between the trade volume and SVI values. There seems to be a small correlation between UK SVI and trade volume. In the next chapter the study uses the Fama-Macbeth method to understand the relation in more a significant manor. Since the data is not lagged, it is possible that stronger links can be found once multiple time variables are introduced into the analysis.

TABLE 13: CROSS-CORRELATION MATRIX OF THE VARIABLES

This table presents the correlation matrix for the sample data consisting of 93 firms from the FTSE AllShare index. The data consists of weekly observations from January 2004 to December 2011.

	Excess Ret.	Ret.	ASVI_UK	SVI_UK (log)	ASVI_Global	SVI_Global (log)	Abnormal Vol.	Vol. (Log)
Ret.	-0,030	1,000						
ASVI_UK	-0,009	-0,012	1,000					
SVI_UK (log)	-0,006	-0,008	0,093	1,000				
ASVI_Global	-0,007	-0,014	0,232	0,038	1,000			
SVI_Global (log)	0,004	0,000	0,030	0,319	0,160	1,000		
Abnormal Vol	0,007	-0,009	-0,038	0,011	-0,036	-0,002	1,000	
Vol (Log)	-0,010	-0,016	-0,008	0,112	-0,013	0,047	0,244	1,000
Market Cap. (Log)	-0,025	-0,009	0,003	0,043	-0,002	-0,032	0,012	0,002

6.3. REGRESSION RESULTS

The following Section describes the results of the different regression tests and discusses the potential reasoning behind the results. In the first Section the paper discusses the Simple OLS regression devised to test the first hypothesis (H1) on the relation between the trade volume and the SVI. The second Section describes the Fama-Macbeth (1973) cross-sectional regression used to test the two hypotheses (H2, H5). The final Section discusses how different robustness checks, such as firm size (H3) and industry (H4), affect the results.

6.3.1. SIMPLE OLS REGRESSION

This Section describes the simple OLS regression conducted to test hypothesis H1.

TABLE 14: OLS REGRESSION RESULTS

This table reports the results from the simple OLS regression. The dependent variable is the log trade volume at times t and t+1. Independent variables are defined in Table 5. *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample size is 93 firms and the period is from January 2004 to December 2011.

	t		t+1	
SVI UK	0,1508***		0,1385***	
SVI Global		0,1427***		0,1311***
Return (raw)	0,2318**	0,2443***	0,1542*	0,1657**
Market Cap. (log)	-0,0037	0,0037	-0,0071	-0,0002
R^2	0,01268	0,02441	0,01601	0,01966

Table 14 depicts the results of the Simple OLS regression with the dependent variable log trade volume (TV) on two different time periods, week t and the next week t+1. The explanatory variables are the search volume (SVI), returns (R) and log market cap (MC)

The regression shows that search volume affects the variable trade volume both on the same week and one week before, with a significance level of 1%. The analysis also shows that returns impact trade volume which is rational and reassures the validity of the results. The third variable market cap does not seem to have any explanatory power in relation to the trade volume, which once again is reassuring, since trade volume in this regression is calculated as trades per day. The effect is positive which means that a higher SVI or return increases trade volume, which is the logical relation and supports the price pressure hypothesis of Barber and Odean (2009).

This result does not yet identify the relative strength between SVI UK and SVI Global. Both produce significant results, and the R^2values are close to each other, although a little higher on the SVI Global regressions.

Based on these results, the H1 hypothesis can be accepted. The analysis finds a simple but significant link between the trade volume and the ticker search volume. This result provides reassurance on the connection between SVI and company shares. In the next section the more complex Fama-Macbeth (1973) regression is presented, which analyzes the predictive power of the SVI on the stock price.

6.3.2. FAMA-MACBETH REGRESSION

This Section describes the Fama-Macbeth (1973) regression conducted to test hypothesis H2 and H5.

TABLE 15: FAMA-MACBETH REGRESSION RESULTS

This table reports the results from Fama-Macbeth (1973) cross-sectional regression. The dependent variable is the future abnormal returns (in basis points) during the first four weeks and during the weeks 5-52. Independent variables are defined in Table 5. All variables are cross-sectionally demeaned (so the regression intercept is zero) and independent variables are standardized (so that the regression co-efficient on a variable can be interpreted as the effect of one standard deviation change). *, ** and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample size is 93 firms and the period is from January 2004 to December 2011.

			ASVI Global		
	Week 1	Week2	Week 3	Week 4	Week 5-52
	(1)	(2)	(3)	(4)	(5)
ASVI - Global	12,5465***	5,7134**	-1,3510	0,6054	-10,2962
Abn Vol.	5,5337**	1,4215*	1,1796	0,4107	3,5209
Log Market Cap.	2,6852	1,3290*	1,0668	2,3475	5,9183
R^2	0,01167	0,02512	0,01991	0,01202	0,01129
			ASVI UK		
	Week 1	Week2	Week 3	Week 4	Week 5-52
	(1)	(2)	(3)	(4)	(5)
ASVI - UK	8,1312*	7,7187*	-2,2920	-5,0054	-6,2421
Abn Vol.	5,5102	1,4143	1,1674	0,4089	3,6353
Log Market Cap.	2,6917*	1,3218	1,0547	2,3354	6,0347
R^2	0,01214	0,02512	0,02195	0,01193	0,01253

Table 15 depicts the Fama-Macbeth (1973) regression, with the depended variable being the future abnormal returns (AR) and independent variables; the abnormal search volume (ASVI), abnormal volume (AV) and log market cap (MC).

There are several findings to be discussed based on these results. Firstly it seems that the study produces somewhat similar results to the reference study conducted by DEG (2011). This study finds that next week's (Column 1) future earnings rise by 12.5 basis points for every one-standard-deviation increase in ASVI Global. This effect is significant at the 1% level for ASVI Global variable and at the 10% level for the UK ASVI. This study also finds slight price reversal in the following weeks, although the effect is not as strong as documented by DEG (2011). The study shows that for ASVI Global, slight price reversal happens at week 3 (Column 3), but during week 4 (Column 4) it returns to having a positive effect. The reversal returns when looking at the rest of the year (Column 5). The regression shows that search volume collected globally (without location filters) is significantly better at predicting abnormal returns compared to results collected from IP-addresses originating from the UK.

Based on these results we can accept the H2 hypothesis, with some conditions, since we do find a significant positive effect between search volume increase today and the share price increase next week. However the study does not produce significant or proportionally meaningful price reversal, so based on this regression the paper cannot conclude that price reversal occurs in the following year.

Looking at the regression in more detail, it is interesting to notice that the predictive power of ASVI Global for the first week is stronger in this study than in DEG (2011), but at the same time the other results and price reversal do not show up with similar significance. Most likely this is due to the fact that this study is run on 93 firms as opposed to the DEG (2011) study which uses nearly 1,500 firms (nearly half of the Russell 3000 stock needed to be omitted due to the lack of data). Due to smaller sample size firm specific effects can dominate the study and thus affect the results. Furthermore it should be noted that consumer-related industries dominated the sample, so there can also be some industry specific effects contributing to the results. However this study does have a longer duration than the reference study and companies that are in the final sample have been screened for excess noise, so the data itself is of high quality, although there are necessary compromises to the quantity due to the arduous SVI data collection process.

Another interesting result to notice is that the SVI values gathered globally are better at predicting the stock prices than those gathered locally. This is a surprising result and contradicts the final hypothesis (H5), in which it was assumed that local results must be subject to less noise, since the amount of different meanings for a ticker symbols would be narrowed down. When analyzing the SVI data collected from the UK, it is clear that the sample is suffering from insufficient amounts of searches. There are very strong peaks in attention, but they do not seem to be strongly correlated with share prices. There are also technical reasons that can affect the results of the UK ASVI. It is possible that the algorithm used by Google to calculate searches originating from the UK is somehow imperfect. It is possible that it omits some searches to ensure data validity, or simple does not work as intended. Since Google does not specify in detail how the filtering function works, it is difficult to further analyze this assumption. There are also user dependent reasons that might affect why the UK ASVI does not perform as well as assumed. Perhaps retail investors travel around the world periodically and are not staying in the UK throughout the year. The IP-address would then shift based on location, resulting in less valid searches in the local markets than globally. An alternative explanation could be that the retail investors have set up their computers to be IP-anonymous or perhaps their security settings do it automatically. Another explanation could be that there are differences in retail investors in the UK and globally. Perhaps UK investors use alternative data sources, such as news sites, blogs or more traditional media such as newspapers. The one thing that is clear from the data is that for some reason there are not enough search queries related to the company, as measured by ticker SVI, originating from the UK based on the Google filter results.

Therefore the fifth hypothesis (H5) must be rejected and conclude that based on this study SVI Global is a better proxy for investor attention and has a stronger predictive power towards share price movements in the UK market.

6.3.3. Robustness checks

This Section describes the three different robustness checks conducted to further analyze the predictive power of SVI. The aim of the robustness checks is gain understanding on the following three different effects; how firm-size (H3), industry (H4) and the time frame affect SVI's predictive power.

For firm-size effects the study hypothesizes (H3), based on the DEG (2011) results, that the effect should be bigger in smaller firms. The reasoning is that small cap firms are more influenced by price pressure (Barber and Odean, 2009) and thus the effect of attention should be stronger. To understand the effect that firm-size has on the SVI, two different portfolios defined as small and large cap are formed. The same analysis as in the previous section is conducted but separately for the two subsamples. The portfolios are not re-adjusted in this robustness check since the consistency would not change significantly in the duration of eight years with the sample companies.

For industry effects the study hypothesizes (H4) that consumer recognizable firms are subject to stronger investor attention, since consumers are aware of them and thus are more inclined to research and invest in them. This assumption is supported both by the availability heuristic and attention theories presented by Barber and Odean (2009). During the study it has already been concluded that the final sample is dominated by consumer centric firms as categorized by the ICB industry codes. The relative amount of consumer service and consumer goods industries increased while forming the final sample compared to their original representation in FTSE AllShare. The reason for the increased representation was that many less consumer-visible industries, such as financial or industry categories, did not receive enough searches for their ticker sign to produce SVI values (Table 10). The study tests to see how consumer recognizable industries are affect by the predictive power of the SVI by dividing the sample companies into two portfolios; consumer visible industries and the rest. The portfolios are not re-adjusted in this robustness check, since none of the 93 companies in the sample receive a new industry code during the time frame of this study.

The final robustness check conducted is to see how two different time frames affect the results. The sample is divided into two separate four year segments; the first subsample consists of data from January 2004 to December 2007, and the second subsample from January 2008 to December 2011. There are two conflicting assumptions that are tested in the robustness check. One is that retail investors exit the equity market during the recession and subsequent downturn of the FTSE AllShare (starting 2008-2009). Thus the results would be weaker for the later subsample since there would be less retail investors. The other assumption is that digital consumption increases as time progresses and users become more accustomed to using the Internet for information gathering. Thus the results would be stronger for the later subsample since there would be more retail investors using Google to search for investment information.

Looking at the subsample’s descriptive data (Table 16) there are a few things to note. Firstly the time frame divided portfolios show that the returns for the post-2007 subsample are much lower and have double the standard deviation compared to the pre-2008 subsample, which indicates the effects of the recession. The other point to note is that the general attention level rises as time goes on, especially in the UK data. The data shows the mean search volume in UK doubling between the two subsamples, which corroborate the findings in Figure 6.

For the industry and market cap cross-sections there are also a few results worth noting. First it seems that the small market cap subsample includes nearly all the consumer recognizable companies, in addition to other small companies. This would indicate that the results will be very similar since consumer recognizable industries, as they are defined in this paper, are also the smaller companies of the subsample. The consumer industry subsample underperforms the other industries with almost four times smaller mean returns during the sample period, which should affect results. Another interesting discovery is that SVI does not seem to be significantly affected by firm industry or size since the mean attention level is very close. This finding is in conflict with the idea that investors are following companies they are familiar with. However since a single robustness check subsample consist of roughly 40-50 companies the implications of the results will not be very strong.

TABLE 16: DESCRIPTIVE STATISTIC OF THE ROBUSTNESS TEST

This table presents descriptive statistics for the three different subsample data consisting of 93 firms from the FTSE AllShare index. The complete data consists of weekly observations from January 2004 to December 2011.

	January 2004-December 2007					January 2008 - December 2011				
	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)
Mean	0,0028	3,0156	0,7927	1,5683	9,2972	0,0013	3,4170	1,4577	1,6577	9,2244
Standard deviation	0,0404	0,9151	0,7951	0,3873	0,8244	0,0732	0,9373	0,4095	0,2179	0,7812
Minimum	-0,3287	0,0000	0,0000	0,0000	7,3663	-0,6513	0,3010	0,0000	0,0000	7,1060
Maximum	0,4090	5,1189	2,0000	2,0000	11,2444	1,2518	8,4651	2,0000	2,0000	11,1822
Total	16326	16326	16326	16326	16326	18843	18843	18843	18843	18843

	Consumer visible industry					Other industries				
	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)
Mean	0,0007	3,3137	1,1436	1,5947	9,3363	0,0025	3,1941	1,1514	1,6256	9,2238
Standard deviation	0,0590	0,8791	0,6975	0,3927	0,6783	0,0608	0,9752	0,7045	0,2676	0,8490
Minimum	-0,5670	0,4771	0,0000	0,0000	7,4605	-0,6513	0,0000	0,0000	0,0000	7,1060
Maximum	0,9138	7,5005	2,0000	2,0000	10,7414	1,2518	8,4651	2,0000	2,0000	11,2444
Total	10751	10751	10751	10751	10751	24417	24417	24417	24417	24417

	Small Cap.					Large Cap.				
	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)	Raw Ret.	Vol.(Log)	SVI_UK (log)	SVI_Global (log)	Market Cap. (Log)
Mean	0,0017	3,2401	1,0727	1,5964	8,6281	0,0022	3,2222	1,2175	1,6339	9,8235
Standard deviation	0,0662	0,9306	0,7282	0,3331	0,4468	0,0544	0,9641	0,6710	0,2897	0,6054
Minimum	-0,5738	0,0000	0,0000	0,0000	7,1060	-0,6513	0,3010	0,0000	0,0000	7,3663
Maximum	1,2518	7,1232	2,0000	2,0000	9,8502	1,0723	8,4651	2,0000	2,0000	11,2444
Total	16630	16630	16630	16630	16630	18538	18538	18538	18538	18538

The robustness test is conducted using SVI Global values, since it was shown to be the stronger variable in the previous section and since it is has more observations than UK SVI for the complete time frame. In the robustness test, the cross-sectional regression is only done for the first week, since it showed to have most of the significant results.

TABLE 17: ROBUSTNESS TEST RESULTS

This table reports the results from Fama-Macbeth (1973) cross-sectional regression. The dependent variable is the future abnormal returns (in basis points) during the first week. Independent variables are defined in Table 5. All variables are cross-sectionally demeaned (so the regression intercept is zero) and independent variables are standardized. *, ** and *** represent significance at the 10%,5%, and 1% level, respectively. The sample size is 93 firms that are divided into subsamples and the sample period is from January 2004 to December 2011.

	Time factor		Industry factor		Size factor	
	Jan.2004-Dec.2007	Jan. 2008-Dec. 2011	Consumer visible	Other	Small Cap.	Large Cap.
ASVI - Global	4,892	11,685	-0.5412	5,527*	2.757	13,183**
Abn Vol.	1,2533**	-0,5823	5.9665	8,163*	1.499**	6,495**
Log Market Cap.	1,065***	0,05334	0.5673	0,629**	1.575***	0.446*
R2	0.05685	0.00597	0.00386	0,02066	0.01412	0.02207

The robustness checks reveal some interesting results. Firstly it is likely that the small subsample sizes are affecting the results since in general significance for the values decreases for all three subsamples. This is especially visible when analyzing the industry effect (H4) based on Industry Category received from DataStream. The R^2 value for the "Consumer Visible" category is over ten times smaller than in the "Other" category. To reliably test the effect of industry or firm size it would be advisable to expand the amount of companies, which in turn would require the user web crawling software. It should also be noted that the ICB industry codes are most likely not a suitable proxy for consumer recognizability, and looking at the robustness test data it would seem that if any one proxy should define how well known a company is, it should simply be size.

When looking at the time factor it seems that the later period (Jan. 2008 to Dec. 2011) looses all predictability, which is most likely due to the more erratic nature of the later period. If the factors affecting share price increase then it is understandable that a singular parameters will lose effectiveness. It can be assumed that the 2008-2009 period affects the stock prices in a way that estimating future returns is more complex, and thus the predictive power of search words diminishes.

The size factor robustness check shows that SVI has a bigger effect on large cap firms which contradicts the findings of DEG (2011). There are multiple reasons for this result. One is that in this specific study the small cap firms underperform in the eight year sample period the large cap firms and therefore the results are affected. If there are fewer returns to predict, then logically the predictive power should suffer. It is also possible that due to poor performance attention has shifted from small firms to larger ones. Another reason is that small cap firms in general do not get as many searches as bigger firms in this specific sample. This might be due to the fact the bigger firms are more interesting to retail investors in the UK market, or simply because the smaller a firm the less known it is. If we assume that bigger companies are more known to investors then it is logical to assume that those are the firms searched for. It is valid to assume investors cannot search for firms they do not know about. Therefore it can be that the results are affected by large cap firms having more reliable and constant search volume indicators whereas small cap firms are subject to more noise. Hence we cannot say that price pressure is stronger for small cap firms (as presented by Barber and Odean, 2009), but neither can we state that price pressure would be stronger for big cap firms. The result seem to indicate that with large cap firms the ticker searches more often represent investor attention towards the company than in small cap firms, and the most likely reasons is that they are more known to the retail investors.

Based on these result we must reject both hypotheses H3 and H4. Based on this sample we cannot conclude that SVI has a stronger effect on small cap firm or consumer centric industries as defined in this study.

7. CONCLUSIONS

This chapter presents the main findings of the paper. The first Section reviews the main findings and summarizes the hypotheses test results. The second Section makes suggestions for further research based on search query data and other original digital data sources.

7.1. SUMMARY OF MAIN FINDINGS

The aim of this paper is to study the link between search volume provided by Google Trends and company shares in the UK. As a reference study this paper uses the article *In Search of Attention* (Journal of Finance, 2011) by Da, Engelberg and Gao. As in the reference study we assume that search volume for a company's ticker symbols is a sign of acute retail investor attention, since institutional investors have more sophisticated tools to use. In the study we assume that a rise in retail investor attention, as measured by weekly search volume, has a positive effect on the share price. The assumption is based on the attention theories of Barber and Odean (2009) who argue that since retail investors own a limited amount of stocks, it is more likely that their attention is towards buying rather than selling. If this is the case then peaks in collective retail investor attention should result in momentary price pressure since the retail demand for the stock rises.

This study finds that there is a significant link between a company's London Stock Exchange ticker search volume and the share's trade volume by conducting a Simple OLS regression. It further finds that the results described by DEG (2011) are also present in the UK market, although the sample produces somewhat different results. By using a cross-sectional Fama-Macbeth (1973) regression the paper finds that a one-standard-deviation increase today in search volume for a company ticker, results in a rise of 12.5 basis points for the company the following week. However this study does not show a significant price reversal at the end of the year, as did the DEG (2011) study. Moreover the paper looks at how the market capitalization, industry and time frame of the sample affect the results. The robustness tests show that the effect of investor attention, as measured by search volume, is more significant in large firms than small ones. This result can be attributed to the small sample size and the fact that a few major companies dominate the sample.

As a new insight the study finds that global search volume is a stronger predictor of company shares than searches originating from the UK. This result is most likely specific for the UK market and the sample period, and should not be assumed to hold in other markets. It is however a significant contribution to the new field of search volume based literature, since it shows that local searches are not more precise by default, although they should be subject to less noise.

To conclude, this study answers the questions *"Can you Google the future?"* with a resounding yes, with the forewarning that as with all new tools it is critical that one understands what they are measuring. As the availability of real-time data on a global scale develops, and its accuracy becomes more refined, the applications for research in finance will undoubtedly grow. There are obvious first-mover pitfalls in approaching new data, such as noise and inflexible systems, but as the first class in finance teaches; with potential risk comes also the potential reward.

TABLE 18: SUMMARY OF HYPOTHESES RESULTS

This table describes the results of the five hypotheses and an explanation for each result.

No.	Statement	Result based on study	Explanation
H1	An increase in a company's tickers Search Volume Index affects the change in trade volume for that company.	Accepted	Simple OLS Regression shows significant explanatory power between SVI and Trade Volume.
H2	An increase in Search Volume Index for a company's ticker has a positive effect in the short-run for that company's share price, but will reverse in under one year.	Accepted conditionally	Fama-Macbeth regression shows that a rise in ASVI today significantly predicts a 12.5 basis point rise in stock price next week. However price reversal effect is not strong enough to accept hypothesis unconditionally.
H3	The effect of the price pressure from retail investor attention is stronger in small companies compared to large companies.	Rejected	The robustness test shows that ASVI effect is stronger in large companies.
H4	Companies with high consumer recognizability are more affected by retail investor attention than companies that are not visible to consumers.	Rejected	The robustness test remains inconclusive due to too small sample size and strong industry under performance. Furthermore the fit of the proxy for recognizability used in this study can be questioned.
H5	The SVI results from UK are better predictors for UK company share price than the SVI results gathered globally.	Rejected	The study finds that global results are stronger at predicting UK company shares.

7.2. SUGGESTIONS FOR FURTHER RESEARCH

The research applications for data received from Google Trends are numerous. It can be used to measure attention as in this paper, but many alternative uses have been presented in the literature review section. SVI has been used as a proxy for investor sentiment, explaining momentum, and increase in company sales to name a few. However almost all research is still based on US data and a relatively short time span. In addition, to my knowledge, there is no research comparing the SVI behavior of different countries.

Another approach is to study word strings in Google Trends and their effect on company performance. There are quite a few studies that focus on how specific wording of news or investor relations correlate with quantitative results; combining that type of study with Google Trends could be very interesting. Since the oldest studies to use this data are only four years old, there are still many fresh ways to use it. Furthermore, the quality and complexity of the data is constantly evolving and with the addition of accessible one-day data frequency or even better geographical location based data, new research topics will undoubtedly arise.

There are currently several private firms sharing data on real-time economic activity in addition to Google; MasterCard, Federal Express, UPS, Intuit or Paypal to name a few. A study based on these firms' data could provide new perspective to previously done research. For instance MasterCard will be opening up anonymous transaction data based on their card purchases. The applications of such a data source are many-fold; for instance studying consumer confidence as measured by daily purchases. Furthermore, there is a continuing trend to open up data to the public, and with the release of new data comes the possibility to do new research. As the options grow and the data becomes richer and more consistent, the choice of using alternative data sources should become more viable. Many of the economic proxies used to measure, for instance Behavioral Finance effects, are ex-post and indirect. As the availability and reliability of real-time data increases, so should its use. In addition to the valuable data offered by the private sector, there is an influx of government data being released. For instance Iceland has shared open API's to all their government data. Although the applications might be to more economic studies, these new data sources should be evaluated.

This study has used data from Google Trends to evaluate investor's attention and its effect on the company shares. However there are alternative measures of attention being discussed in academia. Social media is increasing in popularity as a tool for research and many studies based on attention or sentiment as measured by Facebook posts or Tweets (Zhang et al. 2011) are being conducted. Although alternative new data sources are subject to some first mover challenges, and in general real-time data often generates unwanted amounts of noise, these data sources are also bringing a completely new and fresh perspective to financial research.

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