Stockholm School of Economics
Department of Finance
4350 Master Thesis
Spring Semester, 2016

A Study of Search Interest on Google and Stock Movements

Yeni Li Helgesson (22483) & Yun Hao Lo (40753)

Abstract

This thesis investigates the relation between the search interest of company names from Google Trends and stock movements in five European countries (Sweden, Denmark, Spain, Portugal, and Italy) for weekly and monthly data. Using a sample of OMX Stockholm 30, OMX Copenhagen 20, IBEX 35, PSI 20, and FTSEMIB stocks from September 2006 to March 2016, we find that changes in weekly search interest on Google is neither correlated to return nor to liquidity, but is associated with (1) variations in trading value in all the countries; (2) share turnover only in Sweden and Denmark; (3) price volatility in Spain and Sweden. However, we cannot find the same pattern using monthly data. The latter may be explained by findings in neuroscience about people's dwindling attention span in modern society.

Keywords: Google Trends, Search interest, Investor attention, Stocks

JEL Classification: G15

Supervisor: Anders Anderson

ACKNOWLEDGEMENTS

We would like to thank our supervisor Anders Anderson, Director of the Swedish House of Finance, for his valuable feedback and guidance. We are also grateful for the everlasting support from our families and friends.

TABLE OF CONTENTS

1. Introduction

2. Data

3. Methodology

    3.1 Search Interests of Company Names

    3.2 Stock Data

    3.3 Relation between Search Interest and Trading Activity

        3.3.1 Relation between Search Interest and Trading Value

        3.3.2 Relation between Search Interest and Stock Returns

        3.3.3 Relation between Search Interest and Illiquidity of Stocks

        3.3.4 Relation between Search Interest and Turnover of Stocks

        3.3.5 Relation between Search Interest and Price Volatility

    3.4 Controlling for Trending of Search Interest Data

    3.5 Comparison between Countries

    3.6 Analysis with Monthly Data

4. Results

    4.1 The Results for Weekly Data

        4.1.1 Relation between Search Interest of Company Names and Trading Value of the Stocks

        4.1.2 Relation between Search Interest of Company Names and Turnover of Stocks

        4.1.3 Relation between Search Interests of Company Names and Stock Illiquidity

        4.1.4 Relation between Search Interest of Company Names and Stock Returns

        4.1.5 Omitted Variable Bias

    4.2 The Results after Controlling for Trending of Search Interests

        4.2.1 Relation between Search Interest and Trading Value, Share Turnover, Stock Return and Illiquidity

        4.2.2 Relation between Search Interest and Price Volatility

    4.3 The Results from Monthly Data

    4.4 Discussion

5. Conclusion

Reference

Tables

Appendix

1. Introduction

Variation in share prices is the result of interaction between all market participants. The focus of investors' attention has therefore a strong effect on short-term stock movement (Engelberg et al. 2010). In academia, many asset pricing models assume market efficiency, implying that prices reflect all available information, and thus assets always trade at their fair value (Fama 1976). However, human attention is a scarce cognitive resource (Simon 1971; Kahneman 1973; Crawford 2015). There are thousands of news every day, but investors are not able to absorb every single piece of available information on the market. Moreover, information does not reach its audience immediately, which was particularly true in the past. Before the age of the Internet, traditional media like TV, radio, and newspaper were the main sources of information. These unidirectional channels require their audience to 'be present' in order to receive the information, and make it difficult to measure how fast and how widely the information is spread.

Today with the advance of technology and the proliferation of Internet usage, aggregate investor attention can be captured and quantified by using various online sources such as *Twitter*, *Yahoo!*, or *Google*. The main reason behind it is that when Internet users post or search something online of their own accord, they are undoubtedly paying attention to the particular topic, and their online activities are traceable and measurable.

Mathiesen et al. (2013) provide evidence that trading volumes of public companies and the frequency of the companies' names tweeted on *Twitter* are highly correlated, while Bordino et al. (2012) find that search queries on *Yahoo!* can predict stock trading volumes. *Google* provides powerful and publicly accessible tools like *Google Trends*[1], which displays '**interest over time**', a time series index of terms that users search on Google in a given geographic area. As the Internet has become an integral part of human society and Google being the most widely used search engine[2], Google Trends may offer an useful insight into the relation between investor behaviors and market movements.

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

[2] According to Statista, Google accounts for 88.36% of worldwide desktop market share of search engines in January 2016. http://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/

Choosing the search terms is the first problem one would encounter when using Google Trends as a research tool. There are several methods that have been used by researchers and practitioners. One major approach is to count the number of a specific word appearing in financial books and on websites, or to use tools that identify semantically related keywords. For instance, Preis et al. (2013) select a set of 98 finance-related search terms by using the online edition of *Financial Times* and *Google Sets* (this service is no longer available), and analyze the relationship between search interest and the prices of Dow Jones Industrial Average (DJIA). They find that changes in search interests of finance-related terms could be interpreted as "early warning signs" of stock moves, as significant decrease in DJIA were preceded by an increase in search interest. Applying these warning signs to a hypothetical *'Google Trends strategy'* and backtesting it in DJIA from January 2004 to February 2011, Preis et al. (2013) obtain superior returns from most of the search terms compared to a simple buy-and-hold strategy, with the term *debt* producing the highest return. Likewise, Da et al. (2013) construct a Financial and Economic Attitudes Revealed by Search (FEARS) index by selecting a set of 149 search terms such as *recession* and *bankruptcy* from Harvard IV-4 Dictionary and Lasswell Value Dictionary. They find that the FEARS index can predict short-term return, temporary increases in volatility, and capital flows from equity mutual funds to bond funds in market downturns.

Another widely adopted method to select the search terms is to use the company names, stock tickers, or the index names. Da et al. (2011) propose a direct measure of investor attention using search volume index of Russell 3000 stock tickers from *Google Insights*, a service closed and merged to Google Trends in 2012. They find that the search on Google captures the attention of retail investors and is associated with stock movements. Bank et al. (2011) also report that search interest on Google serves as an intuitive proxy for overall firm recognition; it captures the attention of stock market investors and is associated with trading activity as well as stock liquidity. Takeda et al. (2013) study the relationship between Japanese stock market and search intensity measured by the search interest of company names on Google, and find that search activity is highly correlated with trading value. We argue that this method is more in accordance with investor behaviors in real life, as stockholders are more likely to search the name of the stock they own than to search more broad terms like *debt* or *economics*. Besides, these open terms may be indeed related to macroeconomic developments, but are not as directly related to individual stocks as company

names. Therefore, in this paper we employ search interests of company names as our proxy for investor attention.

While most researches show that stock trading volumes are correlated with corresponding search volumes on search engines and frequencies of appearance on social media, the relation between search interests and stock prices varies. Heiberger (2015) investigates individual stock prices and their connection to firm-specific *Google* search interests, and finds that collective attention in terms of *Google Trends* data serve particularly well as an indicator for "bad news" and subsequent falling prices for companies listed in S&P 100 index, which is consistent with the result of the study on DJIA from Preis et al. (2013). However, in contrast, some papers conclude that increases in *Google* search interest lead to higher stock prices. For example, Da et al. (2011) find that for Russell 3000 stocks short-term higher stock prices follow an increase in search interest, and Bank et al. (2011) also find that in German stock market a rise in search interest is associated with temporarily higher future returns.

Research Motivation and Focus

Some studies have reported that changes in search interest may predict short-term returns, which can be used to build trading strategies. We aim to investigate whether there exists a general relation between investor attention represented by search interest on Google and different aspects of market movement.

Moreover, to the best of our knowledge, most relevant studies focus on a single large market such as US, Germany, or Japan. Our study contributes to these previous researches by examining the relation between search interests of company names and stock movements in relatively smaller countries (Sweden, Denmark, Portugal, Spain, and Italy). In addition, we compare the significance of this relationship in these markets.

Since the financial crisis in 2008, there has been a large disparity between Southern Europe and Northern Europe's economy and stock market performance. Spain, for example, is still struggling with a high unemployment rate of 20.9% (2015 Q4)[3], while the number for Denmark is only 4.5%

[3] Source: http://www.tradingeconomics.com/spain/unemployment-rate

(2015 December)[4]. Likewise, the major stock indices of Spain, Portugal, and Italy are still far below their pre-crisis high, while Denmark's OMX Copenhagen 20 and Sweden's OMX Stockholm 30 have already more than doubled their pre-crisis high in 2015. Therefore, we also study whether the relationship between search interest and stock movements varies from country to country in the past ten years. If it does, we analyze whether the observed effects are more significant for countries that suffer from a more serious and prolonged bear market since the financial crisis or the opposite?

To sum up, the research questions to be answered in this thesis are as follows:

Is search interest from *Google Trends* in Sweden, Denmark, Spain, Portugal, and Italy associated with stock movements, such as trading volume, stock return, share turnover, and illiquidity? And if so, is there any significant difference among our sample of countries regarding the relations between search interest and stock movements?

Our hypotheses are

(1) There are significant relations between search interest from *Google Trends* and stock movements,

(2) There is difference between countries regarding the relation between search interest and stock movements.

Some previous researches study the causality between online searches and stock market movements but fail to conclude that any pattern exists. We argue that the bidirectional relationship is relatively apparent; investors might trade more after finding some information from online searches, and price fluctuations can also prompt investors to search relevant information. Therefore, we only focus on the correlation in this paper.

[4] Source: http://www.tradingeconomics.com/denmark/unemployment-rate

Summary of Study

We investigate stocks that are included in five market indices: OMX Stockholm 30 (Sweden), OMX Copenhagen 20 (Denmark), IBEX 35 (Spain), PSI 20 (Portugal) and FTSEMIB (Italy), and the results of the study are mixed. On one hand, we find that search interest of company names provided by Google Trends has a positive correlation with trading value of corresponding stocks, yet it is significant only for OMX Stockholm 30, OMX CPH 20 and IBEX 35, but not for the other two markets. The significant correlation can only be observed using weekly data, but not monthly data. We conclude that the relation is only temporary. A significant positive correlation between search interest of company names and share turnover exists in the two Nordic markets, but not in Southern Europe markets. We also find significant positive correlation between search interest and price volatility in Spain. On the other hand, no significant relations between search interest and stock return/price or illiquidity are found.

Overall, our results suggest that weekly search interest on Google is associated with trading value and share turnover, but not with return or liquidity. Besides, we find clear difference between the countries, which may be attributed to the disparity of Internet penetration and ostrich effect. No correlation is found using monthly data, and we believe that it is most likely due to people's dwindling attention span in modern society.

2. Data

Google Trends

Google Trends shows the relative popularity of a particular search term to the total search volume on Google across various regions of the world within a selected time period (earliest available data from 2004). The highest number is adjusted to 100 on the trend chart (called 'Interest over time' on Google Trends), and the other numbers represent search interest relative to the maximum point. The reader should note that these numbers do not represent absolute search volume. Besides, Google Trends computes the numbers using a sampling method[5], and therefore the data for the same search term downloaded at different point of time might be slightly different, as discussed by Da et al. (2011, p.1467).[6]

Search terms

The company names are used as search terms in this study after we have carefully reviewed all alternatives adopted by other researchers. Da et al. (2011) use stock tickers as the search terms and argue that two possible problems may occur when using company names instead. First, company names may be searched for reasons irrelevant to investing. For example, people may search "H&M" for shopping purpose. Second, investors might search a company using several variations of its name, such as an abbreviation and a full name. However, we believe it is better to use company names as search terms for stocks listed in smaller markets like those we study in this paper. Take Swedish stock market for example, using tickers of OMX Stockholm 30 stocks as search terms on Google Trends results in a data set with large amounts of 0, meaning that these searches were made by, if any, very few people. This might be due to the fact that Sweden is a small country with a population of only 9.5 million, and naturally online search volumes of stock tickers would be much

[5] According to Google Trends Help, "Google Trends analyzes a percentage of Google web searches to figure out how many searches were done over a certain period of time. For example, if you search for tea in Scotland in March of 2007, Trends analyzes a percentage of all searches for tea within the same time and location parameters."

[6] Da et al. (2011) found that the data downloaded at different points of time might be different, yet the correlations of downloaded data are more than 97%.

fewer compared to other big markets like the US. Hence, using company names would be a better choice here. We further tried adding 'aktie' (meaning stock in Swedish) or 'AB' (a legal form in Sweden and roughly equivalent to the abbreviations Ltd and PLC) after the company names in order to eliminate the noise of irrelevant searches, yet this also leads to the same problem as using tickers. Furthermore, Google Trends actually can filter the results to a certain 'category' to get data for the right version of the search term. Hence, one could in theory simply use the company names and choose the category 'Finance'. However, due to the fact that search interests of company names from Google Trends within category 'Finance' are very low (many zeros), we decide not to select any category and choose to follow the assumption made by Vlastakis et al. (2012) that searches irrelevant to investment purposes are random and should not have a systematic influence. Consequently, we neither add anything to the company names nor select any category in our study.

Regarding the issue of variations of company names, we believe that it is not a major problem for OMX Stockholm 30 stocks (full list of company names used as search terms in this paper is shown in Appendix 1). If investors search, for instance, "Alfa" or "Laval" on Google, the first few items and most of the search results on the first page are something else. In other words, investors would type the full name, "Alfa Laval" in order to get the result they want. As for "TeliaSonera"[7], a telecom company known by and marketed to the public as "Telia", one can easily find it on the top of search results by just googling "Telia". However, when typing "TeliaSonera" on Google Trends, one would see related searches[8] such as "teliasonera ab" ('AB' means limited company in Swedish) and "telia aktie" (Telia stock), while typing "Telia" on Google Trends leads to related searches like "webmail", "bredband" (broadband), and "telia iphone". Consequently, "TeliaSonera" would still be a better choice for this paper.

The discussion above also applies to the other markets we study in this paper.

Sample selection

[7] TeliaSonera changed its name to Telia Company on April 12 2016.

[8] According to Google Trends, "When you search for a term in Trends, you'll see searches related to your term in the "Related searches" section at the bottom of the page."

Small companies are generally less known to the public and thus draw less attention. A company name few people search would lead to a search volume index that contains a large amount of zeros. In order to avoid such problem, we only study Large Cap companies that constitute the major stock index in each country. These indices are: OMX Stockholm 30 (Sweden), OMX Copenhagen 20 (Denmark), IBEX 35 (Spain), PSI 20 (Portugal), and FTSEMIB (Italy). Moreover, since investors tend to have home bias[9] (French et al. 1991) and consequently searches from foreign countries are more likely to be irrelevant to investment purposes, we limit each company's search interest within its home country (for example, 'Sweden' for the company 'Swedish Match').

For each company, we downloaded the time series data of search interest in its home country within group 'Web Search' for the period between September 2006 and March 2016 from Google Trends. The Google Trends data was downloaded in March 2016. Note that data for the same search term downloaded at different point of time might be different as discussed before.

In addition, to ensure that both Google Trends data and stock data are available for each company, we only include companies that meet the following criteria:

1. The company has to be listed on a stock exchange throughout our research period.
2. The company did not change its name during the period.
3. There is enough search volume of the company on Google for Google Trends to calculate the search interest over time.

Take some Nordic companies for example. *Nokia* was listed in OMX Stockholm since 2007 so that Nokia does not have stock data for the whole study period (September 2006 to March 2016), which violates criterion 1. *Fingerprint Card*, a Swedish fingerprint sensor manufacturer, has zero search interest on Google Trends in many weeks between September 2006 and March 2016, which violates criterion 3. *ISS*, a Danish facility service company, was de-listed from Copenhagen Stock Exchange in 2005 and listed again in 2014. Such companies are excluded from our research. Based on the criteria above, the sample for this study includes 28 stocks from OMX Stockholm, 16 stocks from OMX Copenhagen, 27 stocks from IBEX, 10 stocks from PSI, and 21 stocks from FTSEMIB. For full list of companies that we study in this paper please refer to Appendix 1.

[9] Home bias is the tendency for investors to invest most of their wealth in domestic assets, despite the benefits of diversifying into foreign assets.

Stock price, volume, and shares outstanding

Data of price and volume for each company is downloaded from Yahoo Finance between September 2006 and March 2016. The stock prices used in this paper are the adjusted close price (adjusted for dividends and splits) and close price on the last trading day of each week, and the trading volume is the average trading volume in the corresponding week. Close prices are used to calculate trading value together with trading volumes, and adjusted close prices are used to calculate stock returns. Shares outstanding for the stocks are downloaded from WRDS.

Monthly stock data are also downloaded in order to do similar analysis on a monthly basis in order to compare whether the results of analysis based weekly data are robust. Monthly search interests are calculated based on weekly data.

3. Methodology

Two types of data are used for analysis: search interests of company names from Google Trends that represent investor attention, and trading volumes, shares outstanding, close prices and adjusted close prices of stocks that represent stock movements.

The analysis consists of two parts. The first analyzes the general characteristics of respective portfolios and difference between portfolio *Large* and *Small* (3.1-3.2). The second part is to verify the significant of an observed relationship by using regressions (3.3-3.6).

The analysis is done mostly on weekly data, but it is done on monthly data as well in order to see whether the relation, if any exists, is temporary or last over a monthly horizon (3.8).

3.1 Search Interests of Company Names

Weekly search interests of company names are downloaded from Google Trends, then weekly change of search interests are calculated using current week's search interest minus previous week's search interest.

There might exist omitted variable bias when search interest of company names in this study is used as the only explanatory variable. Whether search interest from Google Trends is trending itself has been checked and controlled in analysis.

3.2 Stock Data

Trading value

Based on weekly trading volumes of the stocks, average value of weekly trading value of each stock is calculated by using the following method:

$$TV = \ln(\text{trading volume} * \text{close price}) \quad (1)$$

Then weekly change of trading value for each stock is calculated:

$$TV\ \text{delta}\ (t) = TV(t) - TV(t-1) \quad (2)$$

Stock returns

The return of each stock is calculated by using current week's adjusted close price minus previous week's adjusted close price, divided by previous week's adjusted close price.

$$\text{Ret}(t) = (\text{adjusted close price}(t) - \text{adjusted close price}(t-1))/\text{adjusted close price}(t-1) \quad (3)$$

Illiquidity of company stocks

The illiquidity of a stock shows how easy it is to sell a stock without moving the price. It is a proxy of trading activity. To calculate illiquidity, we use Amihud measure (Amihud, 2002):

$$\text{Illiquidity}(t) = \text{abs}(\text{Ret}(t))/\ln(\text{adjusted close price}(t) * \text{Trading Volume}(t)) \quad (4)$$

Turnover of shares

Turnover of shares is also used as a proxy of illiquidity, but used separately from the illiquidity measure in equation (4):

$$TO(t) = \text{trading volume}(t) / \text{shares outstanding}(t) \quad (5)$$

Volatility of adjusted close price

Weekly volatility is calculated using daily adjusted close price of the week with the following equation. N is the number of trading days of the week t. i is each trading day in the week.

$$\text{Volatility}(t) = \text{std}(\ln(\text{adj close price}(i+1)/\text{adj close price}(i)))*\text{sqrt}(N) \quad (6)$$

3.3 Relation between Search Interest and Trading Activity

3.3.1 Relation between Search Interest and Trading Value

Each week we sort all stocks according to their weekly change of search interest on Google and compute three quantiles with an approximately equal number of stocks, we then analyze average characteristics of the portfolios (portfolio *Large*, *Medium* and *Small*), and difference between the portfolios Large and Small.

OMX Stockholm 30, for example, consists 30 stocks. Firstly, we rank the stocks based on search interest changes, then build 3 portfolios which consists of 10 stocks each. Portfolio Small consists of 10 stocks that have the smallest weekly search interest change, while portfolio Large consists of 10 stocks that have the largest weekly search interest change. If the number of stocks cannot be divided by 3, we try to keep portfolio Small and Large to have same number of stocks, because the difference between these two portfolios is crucial for our analysis.

Secondly, we calculate the average change of trading value of each portfolio by dividing the sum of trading value change of all stocks in the portfolio by the number of stocks. We then get the average change of trading value of portfolio Large, Medium and Small respectively.

The difference of each week's change in trading value between portfolio Large and Small and its average are also calculated.

The significance of the relationship between search interest and trading value is verified by using regression:

$$\Delta\text{trading value (portfolio Large) (t)} - \Delta\text{trading value (portfolio Small) (t)} =$$

$$ß0 + ß1 * (\Delta\text{search interest (portfolio Large) (t)} - \Delta\text{search interest (portfolio Small) (t)})$$

3.3.2 Relation between Search Interest and Stock Returns

Firstly, three portfolios are formed as in 3.3. We calculate the average stock return of each portfolio for each week, such that we eventually obtain the average stock return of each portfolio throughout the entire study period. The weekly difference between portfolio Large and Small is calculated as well.

We further analyze the relations between changes in search interest of each portfolio in week (t) and the average stock return in the same week(t) as well as the following week (t+1).

A regression of weekly differences in the average returns between portfolio Large and Small on the difference of weekly search interest change is used to explore whether the observed relation is significant.

3.3.3 Relation between Search Interest and Illiquidity of Stocks

Three portfolios are formed as described above, and average illiquidity of the stocks in each portfolio for each week is calculated according to equation (4). We then obtain the average value of each portfolio for the entire study period. The difference between portfolio Large and Small is calculated as well. A regression of difference of average illiquidity between portfolio Large and Small on weekly search interest change is used to explore whether the observed relationship significant.

3.3.4 Relation between Search Interest and Turnover of Stocks

The average turnover (TO) of the stocks in each portfolio for each week is calculated according to equation (5). We eventually obtain the average value of each portfolio for the whole study period. The difference between portfolio Large and Small is calculated as well. As we described above, we regress the difference of average turnover between portfolio Large and Small on difference of weekly search interest change.

3.3.5 Relation between Search Interest and Price Volatility

Average change of weekly volatility for each stock is calculated for each of the three portfolios (portfolio Small, Medium and Large). We then compute the weekly differences in the change of volatility between portfolio Large and Small, and analyze its relationship compared to the weekly change of search interest of both portfolios.

3.4 Controlling for Trending of Search Interest Data

Search interest of company names might naturally increase as time passes since internet is becoming more and more popular. We verify whether the search interest data shows trends, and control for those trending series. We conduct a similar analysis in 3.3 and compare the results.

3.5 Comparison between Countries

We compare the relations between search interest and trading value, stock return, illiquidity, turnover, and volatility for different markets, as well as the patterns of change in trading values and share turnover for each country are compared as well.

3.6 Analysis with Monthly Data

Search interests of company names downloaded from Google Trends is weekly data. Weekly data is then converted into monthly data by splitting the search interest series according to how many days of each week belong to a natural month. Taking week Dec 27, 2015 to Jan 2, 2016 as an example, we have five days in the month of December 2015, and two days in the month of January 2016. 5/7 of search interest for the week is attributed to the month December 2015, and 2/7 of the search interest to the month of January 2016. We then download monthly stock data, and conduct the same analysis as for weekly data.

4. Results

4.1 The Results for Weekly Data

First, we report the results for weekly data with the difference of weekly changes in search interest between portfolio Large and Small as the only independent variable.

4.1.1 Relation between Search Interest of Company Names and Trading Value of the Stocks

The trading value is calculated as indicated in equation (1) using trading volume and close prices. The relation between weekly change of search interest of company names at week (t) and trading value of company stocks at both week (t) and week (t+1) is shown in Table 1. The weekly changes of trading value are calculated using equation (2).

In Table 1, we can see that the stocks in portfolio Small have a lower trading value at week (t) in all the markets we analyze, since the average weekly change of trading value is negative for this portfolio. The stocks in portfolio Large tend to have a higher trading value at week (t), because this portfolio has a positive weekly change of trading value in all markets, the portfolio Medium also shows positive weekly changes of trading value, but the change in each market is lower than that of portfolio Large.

The differences of average weekly change of trading value between portfolio Large and Small are positive for all five markets, which means that the trading value of stocks of portfolio Large at week (t) will increase more than correspondent values of portfolio Small. In other words, if the company name has higher increases in search interest, the stock is likely to be more actively traded the same week. We therefore argue that the data suggests a positive correlation between search interest change and trading value change.

Moreover, Table 1 shows that the positive correlation discussed above does not continue the week after, but is likely to reverse. Average changes of trading value for portfolio Small are positive while average changes of trading value for portfolio Large are negative in all five markets. This

means that the trading value for the stocks that had the least change of search interest in week (t) tend to increase in week (t+1), while the stocks that had the strongest increase of search interest in week (t) tend to be less traded the following week. The decrease of trading value for portfolio Large is higher than the increase for portfolio Small, because the difference between portfolio Large and Small is negative.

The positive correlation between the change of trading value and change of search interest during the same week is significant at 10% level for OMX Stockholm 30, and at 5% level for OMX CPH 20 and IBEX 35. The negative correlation between the change of search interest in week (t) and change of trading value in week (t+1) is only significant for PSI 20 at a 10% level. Since no market shows a significant positive correlation between trading value (t), and search interest (t) can also be negatively correlated to the trading value (t+1), we cannot state that the reversed relationship is significant for any market.

4.1.2 Relation between Search Interest of Company Names and Turnover of Stocks

The average turnover of stocks for portfolios Large, Medium, Small and difference between portfolio Large and Small are reported in Table 2.

The average weekly share turnover for the stocks in portfolio Large are higher than those for the stocks in portfolio Small in most of the markets, except for PSI 20. PSI 20 has a slightly negative difference of average turnover between portfolio Large and Small. The positive difference is significant at 5% for OMX Stockholm 30 and OMX CPH 20, while no significant difference is found for the markets in southern Europe.

We can not observe any pattern for average turnover of shares in portfolio Medium. For OMX Stockholm 30, IBEX 35 and FTSEMIB, the average share turnover of portfolio Medium is higher than that of portfolio Small, but the average share turnover of portfolio Medium is lower than that of portfolio Small for OMX CPH 20 and PSI 20.

Table 2 provides some evidence for a negative trend in average turnover a week aftter. The average turnover of stocks in portfolio Large decrease from week(t) to week(t+1), such that the difference

of average turnover between portfolio Large and Small is smaller in week (t+1) than the difference in week (t) for all markets. However, the difference is not significant in any market.

The results from Table 2 show that the average change of search interest and average turnover of shares have a positive correlation for all markets except for PSI20, but the correlation is only significant for the two Nordic markets. This means that the stocks that have the highest increase in search interest tend to have significant higher average turnover of stocks during the same week than the stocks that have shown the weakest increase in search interest for OMX Stockholm 30 and OMX CPH 20. This significant positive correlation tends to disappear the week after, which means that the relation exists only temporary.

4.1.3 Relation between Search Interests of Company Names and Stock Illiquidity

The weekly average illiquidity for stocks is calculated according to equation (4), and the results for all portfolios and the difference of illiquidity between portfolios Large and Small are reported in Table 3.

The results in Table 3 show that the stocks in portfolio Large exhibit a higher illiquidity than the stocks in portfolio Small in week (t) when the portfolios are constructed based on the change of search interest, because the difference of illiquidity between portfolio Large and Small are positive for all markets. The results do show a positive correlation of illiquidity and search interest change in week (t), but this positive difference is not significant for any market.

Intuitionally, if the stocks have higher trading value (from Table 1) when they get more attention, the stocks should be more liquid, so the illiquidity of the stocks should decrease. The results from Table 3 do not follow this intuition, despite that the higher illiquidity of stocks in portfolio Large is not significant, which means that the results do not contradict our intuition in a significant way.

The correlation of illiquidity and search interest change is still positive in week (t+1) for most of the markets except for Italy. The difference of average illiquidity between portfolio Large and Small is much smaller in week (t+1) than that in week (t), because average illiquidity for portfolio Small increase in all markets, while the average illiquidity for portfolio Large decreases. The stocks

in portfolio Large become more liquid from week (t) to week (t+1). The difference between the two portfolios is both positive and significant for OMX CPH 20 and IBEX 35. In this aspect, no significant difference can be observed between markets in southern and northern Europe in week (t+1).

4.1.4 Relation between Search Interest of Company Names and Stock Returns

The relation between weekly change of search interest of company names and the average returns of company stocks in week (t) and week (t+1) for all markets are shown in Table 4

Table 4 shows the relation between weekly average of stock returns and the average change of search interest. The average stock returns for all portfolios and all markets at both week (t) and week (t+1) are negative during the study period. The difference of average returns between portfolio Large and Small is positive for OMX Stockholm 30, but the difference for the markets in southern Europe is negative. None of the differences (either positive or negative) is significant.

From week (t) to week (t+1), average returns for the stocks in portfolio Large become less negative (increased), while average returns for the stocks in portfolio Small become more negative (decreased). If we focus on portfolio Large, the stocks tend to have higher returns in the following week.

4.1.5 Omitted Variable Bias

From weekly results in 4.1, we find some significant correlation, for example between the change of search interest of company names and change of trading value of stocks for OMX Stockholm 30, OMX CPH 20 and IBEX 35. These significant correlations only indicate that a change of search interests and change of trading value tend to increase in the same week, but they do not prove any causal relationship between these two variables.

One problem is a potential omitted variables bias. There might be other variables that both affect trading value of stocks and search interest of company names; for instance, negative information about the markets, or investors are pessimistic about economic situation of particular country.

The results in Table 1 to Table 4 only provide evidence that the series are correlated, and that a high change of search interests may predict higher change of trading value. We cannot say that a higher change of search interest may causes a higher change of trading value because of this omitted variable bias, unless we find all these (hidden) omitted variables that affect the dependent variable and that correlated with our independent variable.

4.2 The Results after Controlling for Trending of Search Interests

Regarding the omitted variable bias discussed in 4.1.5, we analyze if the search interest series are trending. Results are provided in Table 5.

According to Table 5, search interest data for most of the stocks is trending. Thus, the weekly change series of search interests includes the effect of this trend, and the difference of them represents the change in search attention. Table 5 also shows that the coefficients of trends are pretty small, which means the impacts of trending is very weak.

In this section, the results when controlling for trending of search interests are reported and compared with the results in 4.1.

4.2.1 Relation between Search Interest and Trading Value, Share Turnover, Stock Return and Illiquidity

Table 6 to Table 9 show the results of relationship between search interest of week (t) and trading value, turnover of shares, illiquidity and stock returns of week (t) and (t+1) respectively.

When we compare Table 2-4 and 7-9, we can see that the levels do not show significant changes when controlling for trending of search interests. The significance remains at the same level. The correlation between share turnover and change of search interest is significant at a 5% level for OMX Stockholm 30 and OMX CPH 20, which is the same as without any control for trends.

If we compare Table 1 and Table 6, we can see that the correlation between the change of trading value and the change of search interest for OMX Stockholm 30 is still significant at 10% level, whereas the significance increases from a 5% to a 1% level for OMX CPH 20 and IBEX 35.

This provides additional evidence that there is an omitted variable bias in results in 4.1. The results change when we put in one more independent variable (time trending) which is correlated with search interests.

It would be ideal if we could find all omitted variables, but this is almost impossible in reality. For future researches, it would be interesting to study more profoundly if more such variables are found.

4.2.2 Relation between Search Interest and Price Volatility

Table 10 shows the relation between search interest and price volatility, including controls for time trending of search interest.

From Table 10, we can see that for most of the markets except for OMX Stockholm 30, the change in volatility for portfolio Large is higher than that for portfolio Small, and it is significant for IBEX 35 at a 1% level. For OMX Stockholm 30, it is significant at a 10% level, but the magnitude is very small (-0.0003). No significance is found for other markets in week (t).

4.3 The Results from Monthly Data

In order to understand if the mixed results from weekly data hold using monthly data, a similar analysis is conducted with monthly search interest and stock data. The monthly results show no significant relation between search interest and any of trading value, illiquidity, turnover or stock returns. We conclude that trading activity only temporarily responds to changes in search interest (within one or two weeks), and can not be observed over a monthly horizon.

4.4 Discussion

Using weekly data, the data does not provide evidence to establish a clear relationship between search interest and stock returns or illiquidity in all five markets. However, there is a significant positive correlation between weekly search interest of company names from Google Trends and trading value of corresponding stocks for OMX Stockholm 30, OMX CPH 20, and IBEX 35, but not for PSI 20 and FTSEMIB. Moreover, there is positive correlation between search interest of company names and share turnover for the two markets in northern Europe, but none of the markets in southern Europe exhibits this correlation. We argue that this difference might result from the disparity of Internet penetration in those markets. According to World Bank[10], the number of Internet users per 100 people amounts to 96 in Denmark and 92.5 in Sweden in 2014, while the number for Spain, Portugal, and Italy are only 76.2, 64.6, and 62 respectively. Researches have shown that Internet usage has a positive and causal effect on stock market participation (Bogan 2008; Glaser et al. 2013). Consequently, it is not surprising to observe more significant correlation for Sweden and Denmark. Another plausible explanation is related to the ostrich effect[11]. Karlsson et al. (2009) find evidence of a positive relation between the number of logins at accounts and the level of prices. As the stock markets in the southern European countries plunged and have remained low since the financial crisis in 2008, it is likely that stockholders become indifferent to the market, hence trade less regardless of the information they receive from online searches.

On the other hand, we cannot find any relationship between stock movements and search interests of company names using monthly data. This may be due to people's shortening attention span in modern society. It was foreseen decades ago by Nobel Laureate in economics, Herbert Simon, that "a wealth of information creates a poverty of attention" (Simon 1971). Neuroscientists, like Susan Greenfield who published a book about how digital technologies change human brains in 2014, have found the link between shorter attention spans and increasing use of technologies. A research report by Microsoft[12] also supports this argument, showing that the average human attention span

[10] Source: World Bank http://data.worldbank.org/indicator/IT.NET.USER.P2?order=wbapi_data_value_2014+wbapi_data_value+wbapi_data_value-last&sort=desc

[11] In behavioral finance, the ostrich effect is the avoidance of apparently risky financial situations by pretending they do not exist.

[12] https://advertising.microsoft.com/en/.../microsoft-attention-spans-research-report.pdf

had dwindled from twelve seconds in 2000 to eight seconds in 2013, which is shorter than that of a goldfish (nine seconds). Google Trends offers empirical evidence as well. Typing "Panama papers" or "Brussels attacks" in Google Trends, one can find that even these recent world-shocking news only drew very short-term attention. Therefore, it is reasonable that no significant correlation between monthly search interest and stock movements could be found.

Finally, we discuss some potential problems or factors that might impact our analysis. To the best of our knowledge, few if any previous studies consider these potential problems. However, they could have unnegligible impacts on the results.

Measurement error from independent variable (search interest)

When company names are used as search terms, data from Google Trends may include results from searches of brand name or products, etc. There is a limitation to obtain clean data that is only relevant to stock trading.

Impacts of stock splits

Studies show that stock splits result in changes in volatility, liquidity, and trading volume, (Grinblatt et al. 1984; Ohlson et al. 1985; Lamoureux et al. 1987), but it is difficult to quantify and exclude its influence on our study.

Inconsistency of time intervals for Google Trends data and stock data

In Google Trends data the first day of a week is Sunday; i.e., a week for Google Trends data starts from Sunday and ends on Saturday. However, the stock price in this paper is the close price at the last day of each week, and trading volume is the average weekly trading volume. Because the time interval of weekly data from Google Trends is set by Google and we can not adjust it, there is an inevitable inconsistency in the time intervals between stock data and Google Trends data.

Noise in data from Google Trends

It is difficult to eliminate all the noise from irrelevant searches. For example, 'Boliden' is a Swedish mining and smelting company, but it is also a city name. In November 2015, a news about a suspected terrorist in Boliden made the search interest of 'Boliden' on Google surge in this particular period.[13] Such incidents which are unrelated to finance may largely distort the research result. Yet, it is not easy to identify such incidents and to exclude its effect for every single company, especially when all the markets we selected operate in countries where the official language is not English.

Smaller markets, fewer searches

Smaller markets, such as those we study in this paper, have fewer residents compared to large countries like the US, and therefore have smaller amounts of searches on Google. The problem with this is that Google Trends only analyzes data for popular terms and therefore search terms with low volume appear as zero. Da et al. (2011) use tickers of Russell 3000 stocks as the search terms, but in our case, even tickers of the large cap companies in the five European markets generate a data set with large amounts of zero, which might significantly twist the result. Even when using company names as search terms, some series still show significant amounts of zeros and need to be excluded from our study.

Our suggestion for future research is based on sample selections and the comparison of different markets. As discussed in previous sections, reducing the measurement error from irrelevant searches is essential when investigating the relation between stock movements and search interests on Google. This would be of interest for further research to explore the main challenges in detail, such as mitigating the influence of searches irrelevant to stocks while maintaining a Google Trends data set without large amounts of zeros. Moreover, when comparing countries, it would also be interesting to investigate the effect of Internet penetration rate on the relationship between search interests and market movements.

[13] Source: Oro för ökade slitningar i Boliden http://www.sydsvenskan.se/sverige/oro-for-okade-slitningar-i-boliden/

5. Conclusion

By employing a proxy for investor attention using search interests of company names from Google Trends, we investigate the relationship between online searches and stock movements in five European countries (Sweden, Denmark, Spain, Portugal, and Italy) for weekly and monthly data. Our results show that, for Sweden, Denmark, and Spain, weekly search interest on Google is positively correlated with trading value, but neither correlated with return nor liquidity. We also find a positive correlation between search interest of company names and the respective share turnover for markets in Sweden and Denmark, but none of the markets in southern Europe show this correlation. Significant positive correlation between search interest and volatility can also be observed in Spain. We argue that the observed difference is most likely due to the disparity of Internet penetration rate and the ostrich effect. Furthermore, no correlation is found over a monthly horizon, which may be attributed to people's dwindling attention span.

Reference

Amihud Y. (2002). Illiquidity and Stock Returns. Journal of Financial Markets 5 (2002) 31–56.

Bogan, V. (2008). Stock Market Participation and the Internet. Journal of Financial and Quantitative Analysis, 43, pp 191-211.

Bordino I, Battiston S, Caldarelli G, Cristelli M, Ukkonen A, Weber I (2012). Web Search Queries Can Predict Stock Market Volumes. PLoS ONE 7(7): e40014. doi:10.1371/journal.pone.0040014

Curme, C., Preis, T., Stanley, H. E., and Moat, H. S. (2014). Quantifying the Semantics of Search Behavior Before Stock Market Moves. Proceedings of the National Academy of Sciences 111, 11600-11605; DOI:10.1073/pnas.1324054111 (2014)

Crawford, Matthew B. (2015). "Introduction, Attention as a Cultural Problem". The World Beyond Your Head: On Becoming an Individual in an Age of Distraction (hardcover) (1st ed.). Farrar, Straus and Giroux. p. 11.

Da, Z., Engelberg, J., and Gao, P. (2011). In Search of Attention. Journal of Finance, 66(5): 1461-1499.

Da, Zhi and Engelberg, Joseph and Gao, Pengjie (2014). The Sum of All FEARS: Investor Sentiment and Asset Prices. The review of financial studies.

Engelberg, J., Sasseville, C., and Williams, J. (2010). Market Madness? The Case of Mad Money. Management Science, Vol. 58.2012, 2, p. 351-364

Fama, E. F. (1976). Foundations of Finance: Portfolio Decisions and Securities Prices, Basic Books: AZ

Fumiko Takeda & Takumi Wakao (2014). Google Search Intensity and Its Relationship with Returns and Trading Volume of Japanese Stock. Pacific-Basin Finance Journal.

French, K. R., & Poterba, J. M.. (1991). Investor Diversification and International Equity Markets. The American Economic Review, 81(2), 222–226.

Grinblatt, M., Masulis, R., and Titman, S.. "The Valuation Effects of Stock Splits and Stock Dividends." Journal of Financial Economics 13 (December 1984), 461-90.

Glaser, M., Klos, A. (2013) Causal Evidence on Regular Internet Use and Stock Market Participation.

Greenfield, S. (2014) Mind Change: How Digital Technologies Are Leaving Their Mark on Our Brains. Random House. Print.

Galai, D., Sade, O., (2006). The "Ostrich Effect" and the Relationship between the Liquidity and the Yields of Financial Assets. Journal of Business 79

Kahneman, D. (1973). Attention and Effort. Prentice-Hall, Englewood Cliffs, NJ.

Karlsson, N., Loewenstein, G., Seppi D. (2009). The ostrich effect: Selective attention to information. Journal of Risk and Uncertainty, 38(2), pp 95-115

Lamoureux, C. G., & Poon, P.. (1987). The Market Reaction to Stock Splits. The Journal of Finance, 42(5), 1347–1370.

Matthias Bank, Martin Larch & Georg Peter (2011). Google Search Volume and its Influence on Liquidity and Returns of German Stocks.Financial Markets and Portfolio Management.

Mathiesen, J., Angheluta, L., Ahlgren, P. T. H., & Jensen, M. H. (2013). Excitable human dynamics driven by extrinsic events in massive communities. Proceedings of the National Academy of Sciences USA (PNAS), 110(43), 17259-17262.

Ohlson, J. A., Penman, S..(1985) "Volatility Increases Subsequent to Stock Splits: An Empirical Aberration." Journal of Financial Economics 14, no. 2: 251-267.

Preis, T., Moat H. S. & Stanley H. E. (2013). Quantifying Trading Behavior in Financial Markets Using Google Trends. Scientific Reports 3, Article number: 1684.

Raphael H. Heiberger (2015). Collective Attention and Stock Prices: Evidence from Google Trends Data on Standard and Poor's 100. PLoS ONE 10(8).

Simon, H. A. (1971), "Designing Organizations for an Information-Rich World", in Martin Greenberger, Computers, Communication, and the Public Interest.

Vlastakis, N., and Markellos, R. N. (2012). "Information demand and stock market volatility." Journal of Banking and Finance 36(6): 1808-1821.

Tables

Table 1. Average change of trading value of portfolios sorted according to search interest of company names

This table shows average weekly change of trading value of the portfolios. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	Portfolio				
	Small	Medium	Large	Large-Small	
week t					
OMX Stockholm 30	-0.0371	0.0005	0.0338	0.0709	*
OMX CPH 20	-0.0612	0.0103	0.0548	0.1160	**
IBEX 35	-0.0402	-0.0046	0.0462	0.0864	**
PSI 20	-0.0361	0.0216	0.0273	0.0634	
FTSEMIB	-0.0584	0.0002	0.0626	0.1210	
week t+1					
OMX Stockholm 30	0.0116	-0.0069	-0.0097	-0.0213	
OMX CPH 20	0.0071	0.0039	-0.0090	-0.0161	
IBEX 35	0.0057	0.0129	-0.0192	-0.0250	
PSI 20	0.0028	0.0024	-0.0016	-0.0044	*
FTSEMIB	0.0123	0.0138	-0.0236	-0.0359	

Table 2. Average turnover of stocks of portfolios sorted according to search interest of company names

This table shows average turnover of the portfolios. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	Portfolio				
	Small	Medium	Large	Large-Small	
week t					
OMX Stockholm 30	0.0060	0.0068	0.0062	0.0001	**
OMX CPH 20	0.0039	0.0035	0.0044	0.0005	**
IBEX 35	0.0072	0.0073	0.0076	0.0005	
PSI 20	0.0037	0.0032	0.0037	-0.0001	
FTSEMIB	0.0083	0.0087	0.0089	0.0006	
week t+1					
OMX Stockholm 30	0.0061	0.0067	0.0061	0.0000	
OMX CPH 20	0.0040	0.0034	0.0043	0.0003	
IBEX 35	0.0073	0.0074	0.0075	0.0002	
PSI 20	0.0038	0.0031	0.0037	-0.0001	
FTSEMIB	0.0083	0.0091	0.0084	0.0001	

Table 3. Average Illiquidity of portfolios sorted according to search interest of company names

This table shows average illiquidity with Amihud measure of the portfolios. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	change of search interest				
	Small	Medium	Large	Large-Small	
OMX Stockholm 30	0.0017	0.0019	0.0019	0.0001	
OMX CPH 20	0.0019	0.0020	0.0026	0.0007	
IBEX 35	0.0020	0.0021	0.0024	0.0003	
PSI 20	0.0026	0.0026	0.0029	0.0003	
FTSEMIB	0.0022	0.0021	0.0026	0.0004	
OMX Stockholm 30	0.0018	0.0019	0.0018	0.0000	
OMX CPH 20	0.0022	0.0023	0.0021	0.0000	*
IBEX 35	0.0021	0.0022	0.0022	0.0001	*
PSI 20	0.0028	0.0026	0.0028	0.0000	
FTSEMIB	0.0024	0.0022	0.0023	-0.0001	

Table 4. Average stock returns of portfolios sorted according to search interest of company names

This table shows average stock returns of the portfolios. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	change of search interest			
	Small	Medium	Large	Large-Small
OMX Stockholm 30	-0.0027	-0.0040	-0.0024	0.0002
OMX CPH 20	-0.0005	-0.0031	-0.0075	-0.0069
IBEX 35	-0.0026	-0.0032	-0.0059	-0.0033
PSI 20	-0.0022	-0.0032	-0.0052	-0.0030
FTSEMIB	-0.0016	-0.0016	-0.0043	-0.0027
OMX Stockholm 30	-0.0041	-0.0035	-0.0016	0.0025
OMX CPH 20	-0.0034	-0.0070	-0.0021	0.0014
IBEX 35	-0.0027	-0.0044	-0.0046	-0.0019
PSI 20	-0.0040	-0.0019	-0.0041	-0.0001
FTSEMIB	-0.0030	-0.0011	-0.0033	-0.0003

Table 5. Trending of search interests

This table depicts whether series of search interests are trending. Min and max slopes are the smallest and biggest slope of the series which show economic significance of trends. Column 3 shows the number of trending series significant at 1% level out of total number of data series

	slope (min)	slope(max)	trending/total series
OMX Stockholm 30	-0.175	0.125	24/29
OMX CPH 20	-0.061	0.107	15/16
IBEX 35	-0.14	0.16	27/27
PSI 20	-0.029	0.096	9/10
FTSEMIB	-0.046	0.107	18/21

Table 6. Average change of trading value of portfolios sorted according to search interest of company names

This table shows average weekly change of trading value of the portfolios after controlling for trends of search interests. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	Portfolio				
	Small	Medium	Large	Large-Small	
week t					
OMX Stockholm 30	-0.0332	-0.0045	0.0340	0.0672	*
OMX CPH 20	-0.0618	0.0153	0.0521	0.1139	***
IBEX 35	-0.0410	-0.0045	0.0469	0.0879	***
PSI 20	-0.0351	0.0198	0.0272	0.0623	
FTSEMIB	-0.0571	-0.0023	0.0638	0.1209	
week t+1					
OMX Stockholm 30	0.0107	-0.0046	-0.0108	-0.0215	
OMX CPH 20	0.0075	0.0024	-0.0084	-0.0159	
IBEX 35	0.0081	0.0110	-0.0198	-0.0278	
PSI 20	-0.0003	-0.0051	0.0054	0.0057	*
FTSEMIB	0.0117	0.0152	-0.0244	-0.0361	

Table 7. Average turnover of stocks of portfolios sorted according to search interest of company names

This table shows average turnover of the portfolios after controlling for trends of search interests. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	Portfolio				
	Small	Medium	Large	Large-Small	
week t					
OMX Stockholm 30	0.0061	0.0068	0.0061	0.0001	**
OMX CPH 20	0.0039	0.0035	0.0044	0.0005	**
IBEX 35	0.0073	0.0073	0.0075	0.0002	
PSI 20	0.0036	0.0031	0.0039	0.0002	
FTSEMIB	0.0085	0.0087	0.0086	0.0001	
week t+1					
OMX Stockholm 30	0.0061	0.0067	0.0060	-0.0001	
OMX CPH 20	0.0040	0.0034	0.0043	0.0003	
IBEX 35	0.0074	0.0074	0.0073	0.0000	
PSI 20	0.0036	0.0030	0.0039	0.0002	
FTSEMIB	0.0087	0.0090	0.0081	-0.0006	

Table 8. Average Illiquidity of portfolios sorted according to search interest of company names

This table shows average illiquidity with Amihud measure of the portfolios after controlling for trends of search interests. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	change of search interest				
	Small	Medium	Large	Large-Small	
	week t				
OMX Stockholm 30	0.0017	0.0019	0.0019	0.0001	
OMX CPH 20	0.0019	0.0020	0.0026	0.0007	
IBEX 35	0.0020	0.0021	0.0024	0.0003	
PSI 20	0.0026	0.0026	0.0029	0.0004	
FTSEMIB	0.0022	0.0021	0.0027	0.0005	
	week t+1				
OMX Stockholm 30	0.0018	0.0019	0.0018	-0.0001	
OMX CPH 20	0.0022	0.0022	0.0022	0.0000	*
IBEX 35	0.0021	0.0022	0.0022	0.0001	*
PSI 20	0.0027	0.0026	0.0028	0.0001	
FTSEMIB	0.0024	0.0022	0.0023	0.0000	

Table 9. Average stock returns of portfolios sorted according to search interest of company names

This table shows average stock returns of the portfolios after controlling for trends of search interests. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	change of search interest			
	Small	Medium	Large	Large-Small
week t				
OMX Stockholm 30	-0.0032	-0.0033	-0.0025	0.0007
OMX CPH 20	-0.0006	-0.0029	-0.0075	-0.0069
IBEX 35	-0.0029	-0.0029	-0.0058	-0.0030
PSI 20	-0.0021	-0.0035	-0.0051	-0.0030
FTSEMIB	-0.0017	-0.0018	-0.0040	-0.0022
week t+1				
OMX Stockholm 30	-0.0039	-0.0046	-0.0009	0.0031
OMX CPH 20	-0.0036	-0.0048	-0.0033	0.0003
IBEX 35	-0.0024	-0.0048	-0.0045	-0.0021
PSI 20	-0.0038	-0.0032	-0.0036	0.0002
FTSEMIB	-0.0031	-0.0009	-0.0035	-0.0005

Table 10. Average change of volatility of portfolios sorted according to search interest of company names

This table shows average volatility change of the portfolios after controlling for trends of search interests. Portfolio Large consists stocks that have the largest weekly change of search interest of company names. Portfolio Small consists stocks that have the smallest weekly change of search interest, while portfolio Medium includes stocks that have weekly change of search interest between Large and Small (in the middle). Large-Small depicts difference of trading value change between portfolio Large and Small. *, **, *** denote 10%, 5% and 1% significance levels.

Market	change of search interest				
	Small	Medium	Large	Large-Small	
	week t				
OMX Stockholm 30	-0.0002	0.0008	-0.0004	-0.0003	*
OMX CPH 20	-0.0024	0.0015	0.0014	0.0039	
IBEX 35	-0.0015	-0.0006	0.0021	0.0037	***
PSI 20	-0.0019	0.0008	0.0017	0.0036	
FTSEMIB	-0.0022	0.0011	0.0011	0.0034	
	week t+1				
OMX Stockholm 30	0.0009	-0.0007	-0.0003	-0.0012	
OMX CPH 20	0.0003	-0.0002	-0.0001	-0.0004	
IBEX 35	0.0009	0.0010	-0.0018	-0.0028	
PSI 20	-0.0002	0.0007	0.0000	0.0003	
FTSEMIB	0.0002	-0.0002	0.0001	-0.0001	

Appendix

List of search terms for stocks on OMX Stockholm 30, OMX Copenhagen 20, IBEX 35, PSI 20 and FTSEMIB.

Search terms for OMX Stockholm 30 stocks				
ABB	Electrolux	Kinnevik	SEB	Tele2
Alfa Laval	Ericsson	Lundin Petroleum	Securitas	TeliaSonera
ASSA ABLOY	Getinge	Nordea	Skanska	Volvo
Atlas Copco	Handelsbanken	Swedish Match	SKF	
AstraZeneca	HM	Sandvik	SSAB	
Boliden	Investor	SCA	Swedbank	

Search terms for OMX Copenhagen 20 stocks			
Carlsberg	Genmab	Novo Nordisk	William Demant
Coloplast	GN Store Nord	Novozymes	
Danske Bank	Jyske Bank	TDC	
DSV	MAERSK	Tryg	
FLSmidth	Nordea	Vestas Wind	

Search terms for IBEX 35 stocks				
ABERTIS	ENDESA	GRIFOLS	BANCO POPULAR	TELEFONICA
ACS	ENAGAS	IBERDROLA	RED ELECTRICA	MEDIASET
ACERINOX	Fomento de Construcciones	INDRA SISTEMAS	REPSOL	TECNICAS REUNIDAS
ACCIONA	FERROVIAL	INDITEX	BANCO SABADELL	
BBVA	GAMESA	MAPFRE	BANCO SANTANDER	
BANKINTER	GAS NATURAL SDG	OHL	SACYR	

Search terms for PSI 20 stocks		
BCP	JERONIMO MARTINS	SONAE
BANCO BPI	NOS	ALTRI
MOTA ENGIL	PORTUCEL	
IMPRESA	SEMAPA	

Search terms for FTSEMIB stocks				
Azimut	Enel	Italcementi	STMicroelectronics	UniCredit
Banca Mediolanum	Eni	Luxottica	Tenaris	
Banca Monte dei Paschi di Siena	Exor	Mediaset	Telecom Italia	
Buzzi Unicem	Finmeccanica	Saipem	Tod's	
Davide Campari	Assicurazioni Generali	Snam	TERNA	