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What investors are searching for:

Google search volume and its impact on returns and trading activity in Nordic stock markets

Master Thesis in Finance

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Abstract: Google search volume has recently emerged as a novel measure of investor attention to reexamine the relationship between investor recognition and asset prices. By employing naive search queries of company names, this study investigates the effect of variations in Google search volume on stock returns and trading activity in Nordic stock markets. The results indicate that an increase in a stock's local or global search volume is associated with a rise in contemporaneous trading activity, as measured by share volume, dollar volume, and the turnover rate. This effect is particularly strong among the smaller and more illiquid stocks in the sample. This finding further suggests that Google search volume can indeed capture different levels of individual investors' attention. Contrarily, this study does not find significant evidence that Google search volume can predict abnormal returns in Nordic stock markets.

Keywords: Google Trends · Stock Returns · Trading Activity · Nordic Stock Markets

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Contents

1 Introduction

One of the most widely researched topics within financial economics is the predictability of future stock returns. The classic efficient market hypothesis (e.g., Fama, 1970) has since then emerged as a fundamental theory. It claims that asset prices are not predictable since they immediately reflect all available information in an efficient market. As the arrival of new information is random, stock prices must therefore also follow a random path (Fama, 1970). Other research, however, has challenged this traditional view. In particular, Merton (1987) introduces the concept of investor recognition and argues that in an informationally incomplete market, investors are not aware of all available securities. According to risk-return theory, stocks that have lower investor recognition should subsequently offer higher returns in order to compensate their holders for being imperfectly diversified. As investor recognition cannot be directly measured, several proxies have been established in the past, which include news and headlines (Barber & Odean, 2008), the number of published newspaper articles (Fang & Peress, 2009), extreme returns (Barber & Odean, 2008), trading volume (Gervais et al., 2001), and analyst coverage (Lin et al., 2014) among others. These proxies assume that if a stock's name is mentioned heavily in the news media or if trading volume and returns are extreme, then investors must certainly pay attention to the stock. But trading volume and returns can also be driven by factors that are not related to investor attention and just because a news article mentions a stock's name does not guarantee that investors actually read it.

Today's digital environment brings novel measures of investor attention to reexamine the relation between investor recognition and asset prices. Since its introduction, the Internet has revolutionized the production, intermediation, dissemination and consumption of information (Vlastakis & Markellos, 2012). As of January 2020, the Internet records almost 4.54 billion active users, which encompasses 59% of the global population (Clement, 2020). Given its broad reach and easy accessibility at low cost, we would expect the Internet to affect financial markets as well. Nowadays, investors can access information from anywhere and at any time. There is a growing trend among them to turn to the Internet to make informed decisions rather than to pay for advisory services or access to analyst reports (Barber & Odean, 2001).

Instead, they can freely obtain the desired information from financial news websites such as Yahoo! Finance and crowd-sourced content services like seekingalpha.com, among others. In addition, reforms in the securities industry, such as the MiFID II regulation, have led to a decrease in analyst coverage, especially for European small capitalization stocks (Lee, 2018). Since Internet users commonly use search engines to locate and collect information on the web, Internet search queries have emerged as a novel measure of investor attention. Google currently maintains a market share of 87 % (Clement, 2020), dominating the worldwide search engine market. Therefore, search volume reported by Google is likely to be representative of the general public's Internet search behavior (Da et al., 2011). Contrary to previous proxies for investor attention, Google search volume is able to measure and unambiguously reveal actively expressed investor interest. If investors search for a stock using a search engine, they are actively looking for information on the Internet. Google search volume has recently become a popular tool for forecasting a wide range of different economic and financial variables, such as macroeconomic trends and stock market activity. Several studies, for example, find that an increase in a stock's Google search volume leads to either higher (e.g., Bank et al., 2011; Da et al., 2011) or lower (e.g., Bijl et al., 2016) expected stock returns in the short run. Moreover, increased Google search intensity is associated with higher trading volume and improved stock liquidity (e.g., Ding & Hou, 2015; Joseph et al., 2011), as well as higher price volatility (Vlastakis & Markellos, 2012).

This paper contributes to this strand of research by examining the impact of Google search volume on returns and trading activity in the Nordics, which includes the stock markets in Denmark, Finland, Norway, and Sweden. Most previous studies focus on the influence of Google search volume on the U.S. stock market. Analyzing the Nordic stock markets can offer new insights for two main reasons. First, Mathur and Subrahmanyam (1990) argue that Nordic stock markets are likely to be less efficient since they are smaller with relatively few listed stocks compared to bigger, more developed markets. They further reason that information may be less readily available and more costly to acquire due to the markets' sizes and trading structures. Therefore, investors may have a bigger incentive to actively use search engines to acquire information on stocks traded on the Nordic exchanges. In addition, the

Nordic countries report high internet penetration rates ranging from 93% for Sweden to 99% for Norway (Tankovska, 2019), which supports the notion that Nordic investors turn to the Internet for investment advice. Second, Bank et al. (2011) argue that an increase in a stock's Google search volume is related to a decline in stock illiquidity due to a reduction in asymmetric information costs. Butt and Virk (2017) suggest that it is more appropriate to test liquidity-related phenomena in markets that are sufficiently illiquid as opposed to testing them in the U.S. market, which is the most liquid equity market in the world (Bekaert et al., 2007). Besides using a new data set by focusing on Nordic stock markets, this paper further contributes to existing research by simultaneously analyzing a stock's local and global Google search volume as a proxy for investor attention.

By employing naive search queries of company names, this study finds a positive and contemporaneous effect of Google search volume on trading activity in Nordic stock markets. Trading activity is hereby measured by a stock's abnormal share volume, abnormal dollar volume, and abnormal turnover rate in a given month. The relationship is still present after controlling for several firm characteristics and seems to be particularly strong for stocks with a small market capitalization and a high illiquidity ratio. Using portfolio sorts and factor model regressions, this study does not find significant evidence that variations in local or global Google search volume can predict abnormal next month returns in Nordic stock markets.

The remainder of this paper is organized as follows. Section 2 gives a comprehensive overview of the relevant literature. Section 3 and 4 describe the sample data and explain the employed methodology. Section 5 presents and discusses the main empirical results and proposes further robustness tests. Section 6 concludes by focusing on the implications of key findings and giving an outlook on future research.

2 Literature Review

This paper is related to the literature on the effect of investor recognition on stock returns and trading activity, and to the literature on using Google search volume to predict various indicators of stock market activity.

2.1 Investor Recognition and the Stock Market

Previous literature has established that investor recognition can help explain variations in stock returns. The concept of investor recognition, which refers to the number of investors that know about a particular security, was first introduced by Merton (1987). He explains that investors are not aware of all available securities in an informationally incomplete market and that they only choose familiar stocks when constructing their optimal portfolios. As a result, the market for "unrecognized" stocks is relatively small and market clearing can only occur if other investors take undiversified positions in these securities. Investors will consequently demand a risk premium to compensate them for the increased firm-specific risk associated with their positions. Thus, Merton (1987) proposes a long-term negative relationship between investor recognition and stock returns as stocks with lower investor recognition need to offer higher returns in order to compensate their holders for being imperfectly diversified. Barber and Odean (2008) propose a different hypothesis by distinguishing between the buying and selling activity of individual investors as opposed to institutional investors. They acknowledge that big price movements after important, firm-specific news can be linked to increased investor recognition since what caused the price move is likely to have also caught investors' attention. However, they claim that individual investors are more likely to buy rather than sell attention-grabbing stocks. When buying a stock, individual investors are faced with the problem that they can choose from an abundance of investment opportunities. Thus, they tend to limit their search by only focusing on stocks that have recently caught their attention. When selling a stock, on the other hand, individual investors are generally limited to the set of stocks that they already own since they are subject to short-selling constraints. Consequently, individual investors tend to be net buyers of attention-grabbing stocks, which may induce a positive effect on prices in the short run. More recently, Vozlyublennaia (2013) proposes a two-way relationship between investor recognition and stock returns by finding significant interaction effects. Following an increase in investor recognition, she reports notable short-term positive or negative changes in returns. At the same time, a shock to returns, especially if it is negative, leads to long-term changes in attention. Contrary to Barber and Odean (2008), she suggests that individual investors can either induce positive or negative temporary price pressure, depending on the nature of the information that prompted an increase in attention.

Since investor recognition is not directly observable, the empirical study of its effect on financial markets requires the use of some proxy. Previous literature commonly uses media coverage and news stories as a measure of investor attention. Fang and Peress (2009), for example, employ the number of newspaper articles in four daily newspapers in the U.S. and find that stocks with no media coverage earn higher returns than stocks with high media coverage even after controlling for common risk factors. This no-media premium can potentially be linked to Merton's (1987) "investor recognition hypothesis" since wide media coverage may ultimately lead to increased investor attention. Mitchell and Mulherin (1994) study the relation between news announcements reported daily by Dow Jones & Company and measures of financial market activity, such as trading volume and stock returns. They report that a larger number of news announcements contributes to investors receiving more information, which in turn induces increased trading volume and price volatility. However, they only find a weak effect of news coverage on market wide returns, as many news announcements are firm specific and consequently may not have a systematic effect on market indices. Berry and Howe (1994) further use news releases sent by Reuter's News Service to establish a positive relationship between public information arrival and trading volume. In addition, Engelberg and Parsons (2011) find that local press coverage also increases the daily trading volume of a stock. They report a strong relationship between trading activity for a given stock listed on the S&P 500 index and whether local newspapers cover an earnings announcement by the respective firm. Tetlock (2007) more specifically focuses on media sentiment and uses daily news content from a popular Wall Street Journal column to construct a measure of media pessimism. His results show that high media pessimism predicts declining market prices followed by a reversion to fundamentals, and abnormal high or low pessimism predicts high market trading volume. More recently, Garcia (2013) extends these findings by suggesting that news content can help predict stock returns particularly well during recessions as investors' sensitivity to news is stronger in bad times. Other previously proposed measures of investor attention include the volume of stock messages posted on websites such as Yahoo! Finance and Raging Bull (Antweiler & Frank, 2004), and edit frequencies of firms' entries on Wikipedia (Rubin & Rubin, 2010).

All of these media-related proxies make the critical assumption that if a stock's name is mentioned heavily in the news, investors should also pay attention to it. However, an article in a newspaper does not necessarily imply increased investor attention, unless investors actually read it. With the advent of the Internet, novel measures of investor attention have emerged in recent years. According to Joseph et al. (2011), the theory of buyer behavior implies that consumers' active search for information often precedes their purchase decision. Therefore, popular search engines such as Google as well as social media platforms like Twitter and Facebook have become popular tools for providing information on current consumer search behavior. Da et al. (2011) acknowledge that search queries qualify as a more direct and unambiguous measure of investor attention. If investors search for a stock on the Internet via a search engine, they are undeniably paying attention to it. Bank et al. (2011) share this notion and further reason that the significant relationship between contemporaneous trading activity and Internet search volume qualifies the latter as a valid proxy for investor attention. Vozlyublennaia (2013) argues that Internet search queries primarily measure attention from individual investors since they are more likely to use the Internet to search for information on stocks contrary to professional security trades, who will instead use news coverage provided by trading platforms such as Bloomberg.

2.2 Predicting Financial Markets with Google Search Queries

Google has been the most popular search engine worldwide since the early 2000s and continues to be so with a current global market share of 87% (Clement, 2020). Google search activity is consequently deemed to be representative for the general population's search behavior (Da et al., 2011). The firm started to publish search volume data in 2004. It has since then received attention from finance and economic research as Google search queries have been proven useful in forecasting a variety of different macroeconomic and financial variables (Kristoufek, 2013). Bijl et al. (2016), for example, find support for Merton's (1987) hypothesis, which suggests that barely recognized stocks should offer higher returns. In their study of stocks listed on the S&P 500 index, they report a negative relationship between a stock's Google search volume and future returns. However, their trading strategy based on buying stocks with low search volume and selling stocks with high search volume is only profitable when disregarding transaction costs.

Contrary to that, other studies find a positive relation between a stock's Google search volume and short-term returns. In accordance with Barber and Odean's (2008) hypothesis, this temporary effect could be attributed to buying pressure driven by individual investors. Da et al. (2011), for example, use a sample of stocks listed on the Russell 3,000 index and suggest that an increase in Google search volume leads to higher stock prices in the short run and an eventual price reversal within the following year. Further evidence is presented by Joseph et al. (2011). For their analysis of S&P 500 stocks, they find that abnormal returns still persist after controlling for well-known risk factors. With regards to trading activity, they observe that an increase in Google search volume is associated with a higher trading volume. Bank et al. (2011) study the German stock market and support the finding that an increase in Google search volume leads to higher future short term returns and is linked to higher contemporaneous trading activity and a decrease in stock illiquidity. They further argue that Google search queries may primarily catch the attention of individual, uninformed investors as they attribute their finding of improved stock liquidity to a reduction in asymmetric information costs. However, they acknowledge that evidence for an attention-induced return premium, which is not explained by other known risk factors, seems weak. Ding and Hou (2015) also study the impact of individual investors' attention on stock liquidity. They suggest that an increase in a stock's Google search volume significantly expands the shareholder base and improves stock liquidity as it mitigates the information asymmetry problem.

Further research uses Google search volume to predict price movements on a market level. Preis et al. (2013), for example, take multiple keywords relating to financial markets and observe increases in the keywords' Google search volume before stock market falls. They reason that a period of concern usually forgoes bear markets. This general concern may lead investors to gather more information on the market's state, which is then also reflected in increased Internet search activity. Lastly, Kristoufek (2013) focuses on the relation between a stock's Google search volume and its riskiness. He claims that the more frequently investors search for a stock-related keyword, the higher is the risk of that particular stock. By constructing trading strategies that assign lower portfolio weights to stocks with higher search intensities and overweight stocks with lower search intensities, he finds that the strategies are able to reach lower risk levels than an equally weighted portfolio.

To conclude, we would expect that an increase in a stock's Google search volume is linked to higher contemporaneous trading activity. A positive and significant effect would further support the notion that Google search volume can indeed act as a valid proxy for measuring investor recognition in financial markets. Moreover, we would expect Google search volume to have a significant influence on future stock returns. However, there are contradictory results as to whether an increase in search volume leads to higher or lower future stock returns. From the academic literature, two main hypotheses have emerged that can be linked to the different findings. Based on Merton's (1987) "investor recognition hypothesis", we would expect a negative and long-term persistent interdependence between variations in Google search volume and future stock returns. Alternatively, Barber and Odean (2008) suggest that an increase in Google search volume may have a positive short-run effect on stock returns induced by temporary buying pressure from individual investors, which is subsequently reversed for longer periods.

3 Data

The sample consists of all 120 stocks that are currently listed on the NASDAQ OMX Nordic 120 index and spans the period between January 1, 2004 and December 31, 2019. Both the sample size and the sample period are limited to some extent by the availability of Google Trends data. The NASDAQ OMX Nordic 120 index consists of the 120 largest of the 150 most traded shares on the stock exchanges of Copenhagen, Helsinki, Oslo, and Stockholm. The index is chosen to ensure data availability for all sample firms and to make the data collection task manageable.

3.1 Google Trends Data

Google search queries on company names are adopted to proxy for investor attention in Nordic stock markets. Google started publicly reporting a measure of search intensity for any keyword in January 2004 through the Google Trends website.[1] Depending on the time range (e.g., past day, past seven days, past month, etc.), non-real time data is available on a monthly, weekly, daily, and hourly basis, as well as at the global and local level. Google search volume for a specific keyword is not published in absolute terms, but as a relative and scaled value. The absolute number of search queries for a specific keyword is first divided by the total number of search queries for any keyword of the geography and time period specified. For each keyword, the relative values are then further scaled so that the reported data always ranges between 0 (i.e., a period when the search volume for a certain keyword does not meet a designated threshold) and 100 (i.e., the period with the highest relative search volume observed for a certain keyword).

For each stock in the sample, the corresponding time series of monthly Google search volume for the period between January 2004 and December 2019 is manually obtained from the Google Trends website. To further test the robustness of results, the respective weekly Google search volume for the period between May 2015 and December 2019 is also downloaded.[2] If a firm name is rarely searched, Google Trends will return a zero value for that stock's search volume. Observations with a Google search volume of zero in two or more consecutive periods are consequently

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

[2] Weekly observations can only be downloaded for a time range of up to five years.

dropped since the data is invalid and does not provide any meaningful information for the analysis (see also Da et al., 2011; Bank et al., 2011). Of the initial 19,653 firm-month observations, this eventually leaves 17,056 observations for the analysis of local search volume and 18,633 observations for the analysis of global search volume.

In this study, company names as they appear on the official NASDAQ website[3] are employed as search keywords in order to avoid subjectivity. Terms that identify a firm's legal form (e.g., ”AB”, ”A/S”, and ”Oyj”) are generally excluded. The only exceptions are search terms for which obvious ambiguity arises if the legal form is dropped (e.g., ”ISS” and ”Trelleborg”). In these cases, the legal term is kept to ensure a more unambiguous search keyword. For a small number of firms, there is more than one share class listed on the index. The respective share class is then added to the company name and the combined term is employed as a keyword (e.g., ”Atlas Copco A” and ”Atlas Copco B”). Further, six search terms were abbreviated to ensure data availability.[4] According to Bank et al. (2011) and Vlastakis and Markellos (2012), the use of company names instead of stock tickers as keywords helps in deriving a broader and potentially more relevant measure of investor attention. Investors' demand for information is not only associated with the stock, but also with the firm in general. Furthermore, this approach avoids issues when stock ticker names have generic and ambiguous meanings (e.g., ”ALFA”). Nevertheless, the data still includes some irrelevant search queries from people searching for products or support online. Consequently, only a fraction of Internet users who search for a given keyword may actually trade later. This component can be considered as either purely deterministic or random noise (Vlastakis & Markellos, 2012), but it could bias against finding reliable results (Da et al., 2011).

With regards to the geographical scope, the data is first filtered so that only queries within a firm's country of stock market listing are considered. The attention from Nordic Internet users is probably most relevant since only Nordic stocks are considered and investors often prefer to trade on their domestic markets (see also Bank et al., 2011; Preis et al., 2013). Both Bank et al. (2011) and Bijl et al.

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[3] See http://www.nasdaqomxnordic.com/index/.

[4] A list of all firms in the sample and the adopted keywords is presented in Table A1 under Appendix A.

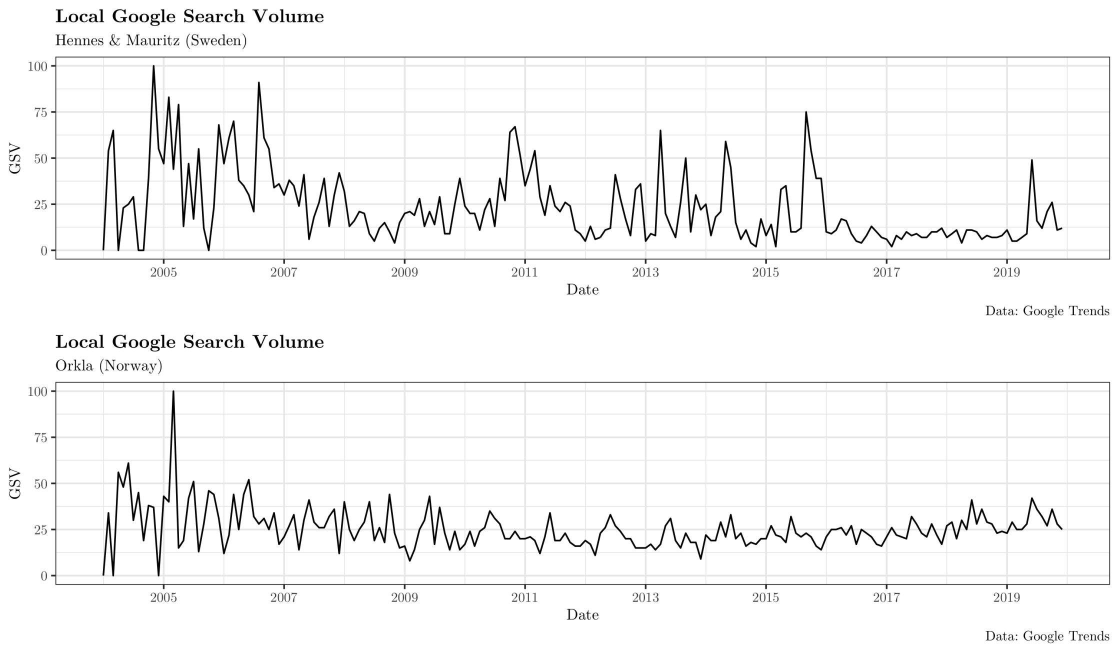


Figure 1: **Illustration of local Google search volume**

This figure plots the monthly local Google search volume for two sample stocks between January 2004 and December 2019. The search terms are "Hennes & Mauritz" and "Orkla", respectively. GSV stands for Google search volume and represents the raw data published by Google Trends.

(2016) acknowledge that using local Google search volume reduces the noise that arises either due to alternate meanings of a keyword in other languages or due to foreign companies with the same name. However, contrary to most previous research using Google Trends data, this study analyzes a sample of stocks that spans four different countries. In addition, Haavisto and Hansson (1992) further suggest that Nordic investors may prefer investing in other Nordic stock markets as a means of diversification due to small transaction costs. Hence, local Google search volume may not fully capture investor attention as it neglects search queries submitted by other "foreign" Nordic investors. Since it is not possible to obtain aggregated search volume data for the four examined Nordic countries, the respective global (i.e., aggregated on a worldwide level) Google search volume for each stock is further downloaded and employed.

Figure 1 plots the monthly local Google search volume for the two search terms "Hennes & Mauritz" and "Orkla" from January 2004 to December 2019. Comparing the two graphs, we can clearly see that the local Google search volume for the term "Hennes & Mauritz" displays a higher variability with more frequent spikes than the term ”Orkla”. Due to the data's scaled nature, all values for a keyword lie between 0 and 100, and data points with a value of 100 represent the period with the highest relative search intensity recorded between 2004 and 2019. For Hennes & Mauritz, the month with the highest Google search volume observed is November 2004. During that month, H&M launched its successful designer collaboration with Karl Lagerfeld, which was sold out immediately in stores across Europe and the U.S. and led to worldwide sales increasing by 24% year-on-year (Boone, 2004). For Orkla, the period with the highest Google search volume reported, March 2005, coincides with its acquisition of Chips Abp, a Scandinavian manufacturer of potato chips (Orkla, 2005). In general, Google search volume is likely to capture increased public attention and subsequently also investor recognition in response to firm specific news (Da et al., 2011).

Although Google search volume has previously been employed in a number of empirical studies, the data also comes with certain drawbacks. First, Google Trends computes search volume using only random samples of all submitted search queries in order to ensure efficient processing. Therefore, the reported search volume for the same keyword can vary slightly when downloaded at different points in time. Da et al. (2011) download Google Trends data for their sample several times and find that correlations between the resulting time series are usually above 97%. They further argue that the effect of such sampling error may bias against finding significant results since they report stronger results for a subset that only includes stocks with a low sampling error standard deviation. Due to privacy considerations, Google Trends further removes searches made by very few people and returns a zero value instead. A truncated sample could ultimately pose a problem for this study. Previous literature suggests that price pressure tends to be stronger among smaller stocks, which on average will also have a lower Google search volume and consequently be removed (Da et al., 2011). Last but not least, Google Trends has revised and improved its reporting of search volume data twice since 2004. In 2011, an improvement to the geographical assignment was applied while in 2016, the data collection system was further altered. Some concerns about the reliability of Google Trends data prior to these changes thus arise.

3.2 Financial Market Data

Financial market data for the period between January 2004 and December 2019 is obtained from Thomson Reuters Datastream. The data includes each stock's daily closing price, total return index, market capitalization, price-to-book value, and number of shares traded and outstanding. Following Fama & French (1992), observations with a negative book value of equity are omitted. Prices, indices, and market capitalizations are denominated in local currencies and are converted to USD at the daily exchange rates. Monthly and weekly USD-denominated returns are further calculated from a stock's total return index, which adjusts for dividend payments. The U.S. one-month T-bill rate is used to calculate excess returns, assuming that a USD-investor can invest in U.S. Treasury bills without incurring any currency risk. This study takes on the perspective of a USD-investor and subsequently ignores potential exchange rate risk (see also Fama & French, 2017). It is thus implicitly assumed that either the absolute purchasing power parity must hold (i.e., relative prices of goods are the same in every country and exchange rates simply represent the ratio of nominal prices of any good in two currencies) or the assets considered cannot be used to hedge exchange rate risk (Fama & French, 2012). Risk factors for the Nordic countries stem from AQR Capital Management's website.[5] The monthly updated data set includes several common risk factors, which are constructed using returns denominated in USD and do not include any currency hedging. Besides providing monthly factor data on a geographically aggregated level (e.g., Global, North America, Europe, etc.), the firm also publishes the factors for individual countries. Following Frazzini and Pedersen's (2014) methodology, aggregate risk factors for the Nordic market are subsequently computed by weighting the respective portfolio for each country in the sample by the country's total lagged (i.e., previous month) market capitalization. Since the data set only includes monthly factors, daily risk factors for the European market are gathered from Kenneth R. French's website[6] and employed in an additional robustness test. Table 1 provides summary statistics on stock characteristics. Panel A relates to all stocks, while Panel B, C, D, and E pertain to Danish, Finnish, Norwegian, and Swedish stocks, respectively.

[5] See https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly.
[6] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1
Summary statistics: Stock characteristics

Variable	Obs.	Mean	Median	Stdev	Min	Max
			Panel A: All stocks			
MV	120	9.20	4.64	13.06	0.01	153.69
BTMV	120	0.56	0.45	0.42	0.00	6.27
P	120	48.39	15.55	204.43	0.19	2,398.25
VO	120	48.75	16.43	93.56	0.00	1,277.19
$*VO*	120	673.44	312.52	1,313.62	0.01	32,735.93
TO	120	0.15	0.08	0.25	0.00	16.24
ILLIQ	120	6.67	0.10	175.92	0.00	14,207.91
			Panel B: Denmark			
MV	23	10.19	5.09	15.19	0.04	118.06
BTMV	23	0.42	0.29	0.38	0.01	3.52
P	23	173.38	29.32	432.34	0.36	2,398.25
VO	23	15.54	7.94	24.69	0.04	256.71
$*VO*	23	513.27	264.30	642.52	0.23	4,937.94
TO	23	0.17	0.08	0.36	0.01	16.24
ILLIQ	23	3.09	0.10	30.71	0.00	1,122.38
			Panel C: Finland			
MV	16	10.53	5.49	14.89	0.67	153.69
BTMV	16	0.53	0.45	0.32	0.08	2.49
P	16	23.62	21.04	13.41	1.92	69.90
VO	16	65.33	21.91	145.26	1.64	1,277.19
$*VO*	16	980.78	474.85	2,398.56	17.28	32,735.93
TO	16	0.13	0.08	0.16	0.02	1.87
ILLIQ	16	0.12	0.07	0.19	0.00	2.87
			Panel D: Norway			
MV	16	11.93	5.16	17.63	0.09	125.14
BTMV	16	0.64	0.53	0.40	0.12	2.92
P	16	15.67	12.52	11.35	1.46	84.13
VO	16	58.23	32.37	87.02	0.00	1,001.24
$*VO*	16	775.33	373.82	1,320.68	0.01	16,435.97
TO	16	0.11	0.06	0.21	0.00	2.49
ILLIQ	16	27.60	0.09	434.51	0.00	14,207.91
			Panel E: Sweden			
MV	65	7.66	4.12	9.35	0.01	65.34
BTMV	65	0.61	0.49	0.46	0.00	6.27
P	65	15.15	12.57	12.10	0.19	116.66
VO	65	54.50	20.18	90.68	0.04	1,162.68
$*VO*	65	620.51	262.91	1,024.85	0.04	18,757.68
TO	65	0.15	0.08	0.23	0.00	3.48
ILLIQ	65	4.04	0.12	83.41	0.00	7,095.86

This table depicts summary statistics for all stocks in the sample and by country of stock market listing. *MV* is the monthly market capitalization in billion USD, *BTMV* the monthly book-to-market value, and *P* the daily closing price in USD. *VO* is the total monthly share volume in million shares, $*VO* the total monthly dollar volume in million USD, and *TO* the total monthly turnover rate. *ILLIQ* is the monthly Amihud (2002) illiquidity ratio, scaled by 10^3.

4 Methodology

Investor attention is proxied by a stock's Google search volume in this study. In order to use the raw data published by Google Trends, a measure of Google search intensity is first constructed. Next, several variables that attempt to quantify trading activity are proposed. The effect of Google search volume on expected returns and contemporaneous trading activity is then examined through portfolio formation and -analysis. Abnormal stock returns are further investigated in a multivariate analysis, using three different factor models to account for various risk factors.

4.1 Measure of Google Search Intensity

Google Trends reports the search volume for any keyword as a value relative to overall search volume in the region and time period specified. On the one hand, the data transformation ensures that the results of this analysis are not driven by a general trend of increased Internet consumption over time (Bank et al., 2011). On the other hand, it prevents the use of the absolute number of search queries for the purpose of this study. Moreover, the relative numbers are scaled so that for each keyword, the data point with the highest relative search volume observed in a specific time period gets assigned a value of 100. Therefore, a comparison of the variation in published Google search volume between all firms in the sample does not reveal any analyzable information. A high value of reported Google search volume for a generally "low search intensity" keyword is not comparable to the same high value of reported Google search volume for a generally "high search intensity" keyword. Instead, the variation in Google search volume within each firm is analyzed.

Following Bank et al.'s (2011) methodology, a stock's signed change in Google search volume is consequently used as a measure of search intensity:

$$\Delta GSV^{i}_{r,\,t} = GSV^{i}_{r,\,t} - GSV^{i}_{r,\,t-1} \tag{1}$$

where $\Delta GSV^{i}_{r,\,t}$ denotes stock i's signed change in Google search volume and $GSV^{i}_{r,\,t}$ its reported Google search volume within region r and time period t. The term "signed change" is used to highlight the direction of change and to prevent any potential confusion with absolute changes. If a stock exhibits a large signed change in one period, this change is either more positive or less negative compared to other stocks' changes during the same period. A small signed change, on the other hand, is associated with a change that is either more negative or less positive compared to other changes. Accordingly, a large and positive signed change in a stock's Google search volume represents an increase in attention and can be compared across the cross-section of stocks in the sample. A small and negative signed change in a stock's Google search volume, on the other hand, is equivalent to a decrease in search intensity and consequently also attention.

4.2 Measures of Trading Activity

In the following, several measures of trading activity are proposed in order to explore how well Google search volume can capture investor attention. Chordia et al. (2001), for example, suggest total share volume and total dollar volume as general measures of trading activity. A stock's total dollar volume during the day is calculated as the number of shares traded multiplied by the respective closing price in USD:

$$\$VO_t^i = VO_t^i \cdot P_t^i \tag{2}$$

where $\$VO_t^i$ denotes total dollar volume, VO_t^i total share volume, and P_t^i stock i's closing price in USD. A higher total share volume and total dollar volume on any given day is consequently associated with an increase in trading activity. Stocks that did not trade on a particular day are assigned a value of zero for share volume and dollar volume, which represents indeed their actual volume on that day (see also Chordia et al., 2001).

Another measure of trading activity is further suggested by Lo and Wang (2000). They use the daily stock turnover rate, the fraction of shares traded relative to the number of shares outstanding on any given day:

$$TO_t^i = \frac{VO_t^i}{NOSH_t^i} \tag{3}$$

where TO_t^i denotes stock i's turnover rate and $NOSH_t^i$ the number of shares outstanding. The turnover rate can be interpreted as the reciprocal of the average holding period of a stock, which means that stocks with a higher turnover rate are on average held for a shorter period of time by investors. In general, a higher turnover rate can be interpreted as an indicator for increased trading activity.

Since several previous studies suggest a positive link between increased investor attention and improved stock liquidity, Amihud's (2002) illiquidity ratio is further investigated (see also Bank et al., 2011; Ding & Hou, 2015). A stock's daily illiquidity ratio is defined as the ratio of the daily absolute return to the dollar trading volume on that day:

$$ILLIQ_t^i = \frac{|R_t^i|}{\$VO_t^i} \tag{4}$$

where $ILLIQ_t^i$ denotes stock i's illiquidity ratio and $|R_t^i|$ the daily absolute return. The ratio gives the price impact (i.e., the percentage price change) per dollar of daily trading volume and acts as a proxy for illiquidity. Hereby, higher values are associated with more illiquid stocks as the price impact of one traded dollar is more severe.

In order to match the daily trading activity measures with the monthly Google search volume data, the daily values are converted into monthly frequency. For share volume, dollar volume and the turnover rate, a stock's daily values for VO_t^i, $\$VO_t^i$ and TO_t^i are summed up for the respective month (see also Bank et al., 2011). For Amihud's (2002) illiquidity ratio, the corresponding monthly value for $ILLIQ_t^i$ is obtained by taking the average over all days in a month, for which data is available (see also Amihud, 2002).

To make these measures comparable across different stocks and time, the effect of Google search volume on abnormal trading activity is of interest in the following analysis (see also Barber & Odean, 2008; Joseph et al. 2011). The average values from a reference period, which consists of the entire calendar year[7], are thus used as a benchmark to determine how unusually large or small trading activity is in a given month (see also Gervais et al., 2001). For each stock in the sample, monthly abnormal trading activity is determined as the relative difference between the value in a given month and its average over the entire calendar year. This procedure is applied to all four proposed measures of trading activity. The abnormal share

[7] Using different reference periods such as a rolling 12 month window or the entire sample period leads to similar results and does not change the main conclusions.

volume is calculated as:

$$AVO_t^i = \frac{VO_t^i - VO_{avg}^i}{VO_{avg}^i} \tag{5}$$

where AVO_t^i denotes stock i's monthly abnormal share volume and VO_{avg}^i the average monthly share volume over the entire calendar year.

Next, the abnormal dollar volume is computed as:

$$\$AVO_t^i = \frac{\$VO_t^i - \$VO_{avg}^i}{\$VO_{avg}^i} \tag{6}$$

where $\$AVO_t^i$ denotes stock i's monthly abnormal dollar volume and $\$VO_{avg}^i$ the average monthly dollar volume over the entire calendar year.

The abnormal turnover rate is derived as:

$$ATO_t^i = \frac{TO_t^i - TO_{avg}^i}{TO_{avg}^i} \tag{7}$$

where ATO_t^i denotes stock i's monthly abnormal turnover rate and TO_{avg}^i the average monthly turnover rate over the entire calendar year.

Lastly, the abnormal illiquidity ratio is calculated as:

$$AILLIQ_t^i = \frac{ILLIQ_t^i - ILLIQ_{avg}^i}{ILLIQ_{avg}^i} \tag{8}$$

where $AILLIQ_t^i$ denotes stock i's monthly abnormal illiquidity ratio and $ILLIQ_{avg}^i$ the average monthly illiquidity ratio over the entire calendar year.

4.3 Univariate Analysis: Portfolio Formation

The portfolio sorting approach has been extensively used in past empirical finance literature in order to identify and explore the relationship between expected returns and multiple different asset characteristics. It is based on the idea that future returns should be either increasing or decreasing as a consequence of some characteristic or feature. Previous studies that employ portfolio sorting use firm size (Banz, 1981), book-to-market ratio (Fama & French, 1992), price-to-earnings ratio (Basu, 1977), and volatility (Ang et al., 2006) among others as sorting variables of interest.

Single-sorted Portfolios

The analysis is commenced with comparing average abnormal trading activity, average stock characteristics, and average stock returns of portfolios, which are sorted on $\Delta GSV^{i}_{r,\ t}$, stocks' signed changes in Google search volume. Local and global Google search volume are first employed individually, and results are compared. According to Fama and French (1992), information on which the portfolio sorting is based on should be known before the returns it tries to explain. In the case of Google Trends, the relevant data on a stock's Google search volume for the previous month is fully available on the first day of each new month. Therefore, stocks are sorted monthly and portfolios are rebalanced accordingly.

Each month, all stocks in the sample are sorted according to their signed changes in Google search volume and three quantiles of approximately equal size are computed. Terciles are employed to ensure an adequate sample size and diversification in each portfolio (see also Fang & Peress, 2009). Each stock is then assigned to one of the three portfolios according to its value of $\Delta GSV^{i}_{r,\ t}$. This procedure results in three portfolios: Small Δ, Medium Δ, and Large Δ, for which Δ denotes "signed changes in Google search volume". For each portfolio, equally weighted averages of contemporaneous abnormal trading activity, monthly stock characteristics (e.g., firm size and book-to-market value), and next month returns are computed and reported.

Da et al. (2011) acknowledge that trading activity is likely to be greater than usual if an unusual number of investors are paying attention to a stock. Therefore, we would expect that an increase in a stock's Google search volume is associated with higher contemporaneous abnormal trading activity. If variations in Google search volume can capture investor attention, the largest difference in abnormal trading activity is expected to be between the Large Δ portfolio and the Small Δ portfolio since they demonstrate large and small signed changes in Google search volume, respectively. Furthermore, based on Merton's (1987) hypothesis, if stocks with lower search intensity earn a return premium, then small signed changes in Google search volume should lead to higher future returns. Contrary to that, according to Barber and Odean's (2008) hypothesis, large signed changes in a Google search volume should lead to higher future short-term returns, and the Large Δ portfolio should consequently outperform the Small Δ portfolio. To investigate whether there is a statistically significant difference in both contemporaneous abnormal trading activity and next month stock returns, two-sample, two-sided Welch t-tests on the differences in means between the Large Δ portfolio and the Small Δ portfolio are performed. Following Vortelinos (2016), Welch t-tests are employed as the two population variances are not assumed to be equal and must therefore be estimated separately. The test statistic is specified as follows:

$$t = \frac{\bar{x}_L - \bar{x}_S}{\sqrt{\frac{s_L^2}{n_L} + \frac{s_S^2}{n_S}}} \tag{9}$$

where $\bar{x}_L$ and $\bar{x}_S$ denote sample means, s_L^2 and s_S^2 sample variances, and n_L and n_S sample sizes for the Large Δ portfolio and the Small Δ portfolio, respectively. Point estimates for the differences are reported together with 95% confidence intervals. The 95% confidence intervals are further calculated as:

$$(\bar{x}_L - \bar{x}_S) \pm c \cdot \sqrt{\frac{s_L^2}{n_L} + \frac{s_S^2}{n_S}} \tag{10}$$

where the constant c is the 97.5th percentile in a Student's t-distribution with degrees of freedom calculated according to the Welch-Satterthwaite equation.[8]

Double-sorted Portfolios

To address concerns that the results of the univariate analysis are driven by various firm characteristics, the robustness of the results is investigated based on presorted portfolios (see also Fang & Peress, 2009). Through conditional sorting, the double-sorted portfolios control for firm size, book-to-market value, current month return, and stock illiquidity one at a time. Each month, the stocks are first sorted into terciles according to the highlighted firm characteristics. Each characteristic-based tercile is then further split into three portfolios of equal size based on the stocks' signed changes in Google search volume. For each characteristic-based presorted portfolio, this procedure eventually results in nine Google search volume subportfolios of approximately equal size. Equally weighted averages of contemporaneous

8 A derivation of the Welch-Satterthwaite equation is presented under Appendix B.

abnormal trading activity and next month returns for each of the nine subportfolios are computed and reported together with the differences in means for the Large Δ and Small Δ portfolios.

4.4 Multivariate Analysis: Factor Models

To analyze abnormal stock returns controlling for various risk factors, three different factor models are examined in the following: the market model, the Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model. In general, a factor can be described as a variable or characteristic with which asset returns are considered to be correlated. More specifically, factor models explain the expected return on an asset (or portfolio) as a linear function of the risk of the asset (or portfolio) with respect to a number of systematic risk factors. These risk factors represent undiversifiable risk for which investors require a higher rate of return for bearing it.

The market model is based on the capital asset pricing model (CAPM), which was first introduced independently by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966) and has since then been widely applied in practice. According to the CAPM, an individual asset's risk premium is solely determined by its exposure to market risk (β_i). The regression equation is thus specified as follows:

$$r_t^i - r_t^f = \alpha_i + \beta_i(r_t^M - r_t^f) + \varepsilon_t^i \tag{11}$$

where r_t^i denotes asset i's return, r_t^f the risk-free rate, and r_t^M the return on the market. However, today's research predominantly rejects the CAPM assumptions and argues that one factor is not sufficient in properly explaining asset returns.

The Fama-French (1993) three-factor model can be described as an extension of the CAPM. It aims to explain stock returns through three factors, namely market risk (i.e., the market factor), the outperformance of small-capitalization firms relative to large-capitalization firms (i.e., the size factor), and the outperformance of high book-to-market value firms relative to low book-to-market value firms (i.e., the value factor). The main idea is that the market tends to regularly pay higher returns for small size and high value stocks. The regression equation is specified as follows:

$$r_t^i - r_t^f = \alpha_i + \beta_i(r_t^M - r_t^f) + s_i(r_t^{SMB}) + h_i(r_t^{HML}) + \varepsilon_t^i \tag{12}$$

where s_i and h_i represent an asset's exposure to size and value risk. Further, SMB and HML are zero-cost portfolios that buy small stocks and sell big stocks and buy high book-to-market stocks and sell low book-to-market stocks, respectively.

Lastly, the Fama-French (1993) three-factor model is extended by including a momentum factor as proposed by Carhart (1997), which results in the Carhart (1997) four-factor model. The momentum factor tries to capture the short-term tendency that stock prices continue to rise if they have been performing well and that they continue to decline if they have been performing badly. The regression equation is specified as follows:

$$r_t^i - r_t^f = \alpha_i + \beta_i(r_t^M - r_t^f) + s_i(r_t^{SMB}) + h_i(r_t^{HML}) + w_i(r_t^{WML}) + \varepsilon_t^i \tag{13}$$

where w_i represents an asset's exposure to the momentum factor and WML is a zero-cost portfolio that goes long in previous "winner" stocks and short in previous "loser" stocks.

Each month, all stocks are sorted into three quantiles of approximately equal size according to $\Delta GSV_{r,\ t}^i$, a stock's signed change in Google search volume. Following the methodology of Fang and Peress (2009), two different trading strategies are proposed that are based on the results for average next month returns from the univariate analysis. Using local Google search volume, a zero-investment strategy is constructed, which goes long in a portfolio of stocks with small signed changes in search volume (Small Δ) and short in a portfolio of stocks with large signed changes in search volume (Large Δ) (see also Bijl et. al, 2016). This strategy is based on Merton's (1987) investor recognition hypothesis and implies that stocks with low Internet search intensity should outperform stocks with high Internet search intensity in order to compensate investors for being imperfectly diversified. A second strategy is tested for global Google search volume, for which the long- and the short position is reversed (see also Bank et al., 2011). According to Barber and Odean (2008), buying pressure from individual investors should lead to higher future short-term returns for stocks with large signed changes in Google search volume. The long and short positions in each strategy are equally weighted and held for one month following portfolio formation. Portfolios are rebalanced monthly, based on the publication of new Google Trends data. The next month returns on the zero-cost portfolios are then computed. The time series of equally weighted average returns is regressed on the constructed risk factors for the Nordic stock market. Nordic risk factors are hereby employed as previous literature suggests that domestic versions of the factor models may better explain the time-series variation in portfolio returns than global versions (Griffin, 2002). Any difference in returns between stocks with large and small signed changes in Google search volume may be due to exposure of the zero-investment strategies to the risk factors accounted for by the models. In this case, the intercept estimates of the factor model regressions should not be significantly different from zero. However, if an attention-induced return premium exists, the zero-investment strategies should generate excess returns, which cannot be explained by common risk factors. Lastly, returns in excess of the risk-free rate (i.e., portfolio returns minus the U.S. one-month T-Bill rate) are examined separately for the long- and short positions.

5 Empirical Results

This section focuses on the results of the aforementioned analysis on the relationship between variations in Google search volume, stock returns and trading activity in Nordic stock markets. Average characteristics of single- and double-sorted portfolios based on signed changes in Google search volume are first examined. Next, three different factor models are analyzed to further examine abnormal stock returns when controlling for well-known risk factors. Lastly, several robustness tests are presented, and study limitations are discussed.

5.1 Single-sorted Portfolios

Each month, stocks are first sorted into terciles according to their signed changes in Google search volume. Average stock characteristics for the three Google search volume portfolios Small Δ, Medium Δ, and Large Δ are reported in Table 2. Table 3 further presents the coefficients from regressions of portfolio excess returns in the month following formation on recognized risk factors for the Nordic market. Panel A and B report the values when sorting is based on local Google search volume and global Google search volume, respectively.

Local Google Search Volume

First, only a stock's local Google search volume is considered when conducting the monthly portfolio sorts. Looking at the first three rows in Panel A of Table 2 labeled ***AVO***, ***\$AVO***, and ***ATO***, the average values for the three measures of abnormal trading activity uniformly increase when moving from the Small Δ portfolio to the Large Δ portfolio. Moreover, the differences in means between the two portfolios are statistically significant at the 1% level. Stocks with large signed changes in local search volume display an abnormal share volume that is on average 3.03 percentage points higher per month than the abnormal share volume of stocks with small signed changes in local search volume. Similarly, such stocks show an abnormal dollar volume that is on average 2.92 percentage points higher, and an abnormal turnover rate that is on average 3.48 percentage points higher. With regards to Amihud's (2002) illiquidity ratio, the negative sign of ***AILLIQ*** for the Large Δ portfolio indicates that large signed changes in Google search volume are accompanied by a contemporaneous decrease in illiquidity as smaller values for ***ILLIQ*** are associated with more liquid stocks. However, the difference in means between the Large Δ portfolio and the Small Δ portfolio is not significantly different from zero.

The row labeled ***RET*** shows that the average next month returns for stocks in the Small Δ, Medium Δ, and Large Δ portfolios are 1.48%, 1.48%, and 1.31%, respectively. The average return differential of 0.17% per month between stocks with small signed changes and stocks with large signed changes in local search volume is hereby not statistically significant.

Moreover, the average firm size of stocks in the Medium Δ portfolio is different from the firm size of stocks that display small or large signed changes in local search volume. While stocks in the Small Δ and Large Δ portfolio have an average market capitalization (***MV***) of 8.95 and 8.42 billion USD, respectively, the average market capitalization of stocks in the Medium Δ portfolio amounts to 10.87 billion USD. Furthermore, the average difference in market capitalization between the Large Δ portfolio and the Small Δ portfolio is positive and statistically significant at the 5% level. This suggests that it is particularly the smaller stocks in the sample that exhibit large signed changes in their local Google search volume.

Panel A of Table 3 presents parameter estimates for the three factor models when portfolio excess returns are regressed on the respective risk factors for the Nordic market. For the Small Δ portfolio, the positive and significant coefficient on ***HML*** in the Fama-French (1993) three-factor model shows that the portfolio has a positive exposure to value stocks. The negative and significant coefficients on ***WML*** in the Carhart (1997) four-factor model, on the other hand, indicate that stocks with small and medium signed changes in local search volume have a negative exposure to momentum stocks. For the Large Δ portfolio, this coefficient becomes positive, albeit statistically insignificant.

Global Google Search Volume

When sorting is based on signed changes in a stock's global Google search volume, the results for abnormal trading activity are similar to those when local Google search volume is employed. Panel B of Table 2 shows that the average values for

Table 2
Single-sorted portfolios: Stock characteristics

	Δ Search Volume			Difference	95% CI	
Variable	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
			Panel A: Local Google search volume			
AVO	−0.67	0.40	2.36	3.03***	1.58	4.48
$*AVO*	−0.42	0.35	2.50	2.92***	1.45	4.39
ATO	−1.13	0.56	2.35	3.48***	1.93	5.02
AILLIQ	−0.06	0.06	−0.61	−0.55	−2.08	0.98
RET	1.48	1.48	1.31	−0.17	−0.53	0.19
MV	8.95	10.87	8.42	−0.53**	−1.00	−0.07
BTMV	0.53	0.58	0.54	0.01	−0.01	0.02
			Panel B: Global Google search volume			
AVO	−0.29	−0.54	3.26	3.55***	1.97	5.13
$*AVO*	−0.18	−0.54	3.33	3.50***	1.90	5.11
ATO	−0.56	−0.57	3.36	3.92***	2.26	5.57
AILLIQ	−0.18	0.21	−0.32	−0.14	−1.63	1.36
RET	1.35	1.47	1.66	0.31*	−0.03	0.65
MV	9.20	11.09	8.21	−0.99***	−1.44	−0.54
BTMV	0.54	0.56	0.55	0.01	−0.01	0.02

This table depicts average stock characteristics of monthly portfolios, which consist of stocks sorted according to their signed changes in Google search volume. For each portfolio, equally weighted averages of contemporaneous monthly abnormal trading activity, monthly stock characteristics, and next month returns are computed. *AVO* is the contemporaneous abnormal share volume, $*AVO* the contemporaneous abnormal dollar volume, *ATO* the contemporaneous abnormal turnover rate, and *AILLIQ* the contemporaneous abnormal illiquidity ratio in %. *RET* gives the one-month return in %. *MV* is the market capitalization in billion USD and *BTMV* the book-to-market value. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

the variables *AVO*, $*AVO*, and *ATO* are consistently higher for stocks in the Large Δ portfolio than for stocks in the Small Δ and Medium Δ portfolios. For all three measures, the differences in means between the Large Δ portfolio and the Small Δ portfolio are statistically significant at the 1% level. For abnormal share volume, abnormal dollar volume, and the abnormal turnover rate, the differences amount to 3.55%, 3.50%, and 3.92% per month, respectively. The average difference in abnormal stock illiquidity, *AILLIQ*, between stocks with large signed changes and stocks with small signed changes in global search volume is statistically insignificant.

The average next month returns for stocks with small, medium, and large signed changes in global search volume are 1.35%, 1.47%, and 1.66%, respectively. Contrary to the findings for local search volume, the Large Δ portfolio outperforms the Small Δ portfolio by on average 0.31% per month (3.78% per year) when stocks are sorted

Table 3
Single-sorted portfolios: Risk factor exposures

Coefficient	Small Δ	Medium Δ	Large Δ
	Panel A: Local Google search volume		
CAPM			
$MKT-RF$	1.0081***	1.0235***	0.9976***
FF-Three-Factor			
$MKT-RF$	1.0077***	1.0196***	1.0024***
SMB	0.0766	−0.0095	0.1032
HML	0.1104*	0.0942	0.0057
C-Four-Factor			
$MKT-RF$	0.9681***	1.0057***	1.0037***
SMB	0.0376	−0.0231	0.1045
HML	0.0620	0.0772	0.0073
WML	−0.2393***	−0.0837**	0.0080
	Panel B: Global Google search volume		
CAPM			
$MKT-RF$	1.0000***	1.0228***	1.0098***
FF-Three-Factor			
$MKT-RF$	1.0017***	1.0204***	1.0126***
SMB	0.1201**	0.0090	0.1059*
HML	0.0998*	0.0759	0.0626
C-Four-Factor			
$MKT-RF$	0.9916***	0.9962***	0.9980***
SMB	0.1101*	−0.0148	0.0915*
HML	0.0875	0.0463	0.0448
WML	−0.0609	−0.1463***	−0.0882**

This table depicts the coefficients from regressions of portfolio excess returns in the month following formation (i.e., next month portfolio return minus one-month U.S. T-Bill rate) on recognized risk factors for the Nordic market. The portfolios consist of stocks, which are sorted according to their signed changes in Google search volume. Three different factor models are presented. $MKT-RF$ denotes a portfolio's exposure to the market factor, SMB its exposure to the size factor, HML its exposure to the value factor, and WML its exposure to the momentum factor. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

according to their signed changes in global search volume. This return differential is statistically significant at the 10% level.

With regards to the average market capitalization of the three portfolios, the findings for global search volume mirror the findings for local search volume. Stocks in the Medium Δ portfolio display on average a higher market capitalization than stocks in the Small Δ and Large Δ portfolios. Moreover, stocks in the Large Δ portfolio have a market capitalization that is on average 0.99 bn USD lower per month than stocks in the Small Δ portfolio. This difference is statistically significant at the 1% level. On average, it is thus the smaller firms that exhibit large signed changes in global search volume.

Focusing on the factor model coefficients, Panel B of Table 3 indicates that the Small Δ portfolio and the Large Δ portfolio have a positive and significant exposure to small stocks according to the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. In contrast to the results for local search volume, it is now the Large Δ portfolio that shows a significant negative exposure to momentum stocks.

Analysis of Single-sorted Portfolios

With regards to the relation between Google search volume and contemporaneous trading activity, the sorts based on local search volume or global search volume report similar results. In both cases, they point to a positive relationship as averages of abnormal share volume, abnormal dollar volume, and the abnormal turnover rate uniformly increase when moving from the Small Δ to the Large Δ portfolios. The respective differences in means between the Large Δ and the Small Δ portfolios are all statistically significant at the 1% level. While this study examines a contemporaneous relationship between Internet search intensity and trading activity, Da et al. (2011) report that Google search volume is a lead indicator for trading activity, suggesting that investors trade only after paying attention to a particular stock. In an additional analysis, the average values of the three measures in the month following portfolio formation are compared. The results for next month abnormal trading activity are presented in Table C1 under Appendix C. While the average differences between the Large Δ and the Small Δ portfolios are still positive and mostly significant at the 10% level, they become smaller in magnitude. Nevertheless, this finding does not necessarily contradict that of Da et. al (2011) since they study weekly as opposed to monthly variation in Google search volume and trading activity. A stock that records a surge in search volume in one week may not exhibit higher abnormal trading activity until the next week. However, the same inference may not apply to a longer time horizon. The conclusion that variation in a stock's Google search volume has a significant effect on trading activity as measured by abnormal share volume, abnormal dollar volume, and the abnormal turnover rate is supported by previous research (e.g., Bank et al., 2011; Da et al., 2011; Joseph et al., 2011). It further reinforces the notion that search queries not only capture general Internet users' attention, but are also related to trading activity and consequently to investor recognition. The results for abnormal stock illiquidity indicate that there does not seem to be a significant contemporaneous effect of Google search volume on changes in stock illiquidity as measured by Amihud's (2002) ratio. This finding differs from Bank et al. (2011), who report that the liquidity of stocks with large signed changes in search volume improves significantly compared to stocks with small signed changes in search volume. While Ding and Hou (2015) find a positive and significant relationship between Internet search intensity and stock liquidity using bid-ask spreads, this relation becomes insignificant when employing Amihud's (2002) ratio. They attribute this result to the assumption that Google search volume mostly reflects the attention from individual as opposed to institutional investors. As the traded dollar volume per transaction tends to be lower for individual investors, their trading behavior is less likely to have a significant impact on the stock price, as measured by Amihud's (2002) illiquidity ratio. Moreover, Amihud (2002) also acknowledges that there are more precise and better measures of illiquidity, such as quoted or effective bid-ask spreads, transaction-by-transaction market impact or the probability of information-based trading. However, these measures require a high amount of microstructure data, which is often not available for many stock markets. Although previous studies report a strong empirical relation between trading volume and stock liquidity (e.g., Stoll, 2002), the findings for abnormal share volume, abnormal dollar volume, and the abnormal turnover rate do not automatically contradict those for the abnormal illiquidity ratio. Chai et al. (2011), for example, argue that stock liquidity is a multifaceted concept and different proxies may only capture single aspects of it.

The results for next month returns when sorting is based on local search volume differ from those when sorting is based on global search volume. In the case of local search volume, the difference in mean returns between the Large Δ portfolio and the Small Δ portfolio is negative, albeit statistically insignificant. The opposite is shown in the case of global search volume, as stocks in the Large Δ portfolio earn on average higher next month returns than stocks in the Small Δ portfolio (see also Bank et al., 2011; Da et al., 2011; Joseph et al., 2011). This return differential is hereby statistically significant at the 10% level. The finding would be consistent with

Barber and Odean's (2008) hypothesis, who suggest that temporary buying pressure from individual investors leads to higher short-term returns for stocks with increased investor attention. However, due to the contrary findings for local and global search volume and only weak statistical significance in the case of global search volume, this result should be interpreted with caution.

In both cases, it is particularly the smaller firms in the sample that exhibit on average large signed changes in Google search volume. This finding is in line with Bank et al. (2011), who report similar results for their study on the German market.

The exposure to momentum stocks differs for the two portfolios depending on whether sorting is based on local search volume or global search volume. While the coefficient on WML is negative and significant for the Small Δ portfolio in the case of local search volume, it is the Large Δ portfolio that reports a negative and significant coefficient in the case of global search volume. The finding based on local search volume is supported by Da et al. (2010), who suggest that the momentum effect is much weaker among stocks with lower Google search volume. They argue that individual investors, whose attention is captured by Internet search queries, are more likely to suffer from overconfidence and other behavioral biases. According to Daniel et al. (1998), momentum in stock markets is generated by investors being overconfident about private information they possess, thus pushing prices above their fundamental values. Therefore, stocks with small signed changes in local search volume may be less exposed to momentum caused by overconfident individual investors.

5.2 Double-sorted Portfolios

Each month, stocks are first sorted into terciles based on various firm characteristics (i.e., firm size, book-to-market value, current month return, and stock illiquidity). The stocks in the resulting three portfolios are then further sorted based on their signed changes in Google search volume. Table 4 reports the average contemporaneous abnormal dollar volume of the nine subportfolios while Table 5 presents the average next month portfolio returns. As dollar volume is one of the most widely used measures of trading activity (Bank et al., 2011), the abnormal dollar volume is chosen to be representative for abnormal trading activity in the following analysis. The results for abnormal share volume, the abnormal turnover rate, and the abnormal illiquidity ratio are presented in Tables C2-C4 under Appendix C.

Local Google Search Volume

With regards to the relationship between local Google search volume and contemporaneous trading activity, the double-sorts generally support the unconditional results. Panel A of Table 4 shows that stocks with large signed changes in local search volume continue to experience on average a higher abnormal dollar volume than stocks with small signed changes in local search volume, even after controlling for several firm characteristics one at a time. With only few exceptions, the differences in means between stocks in the Large Δ portfolios and stocks in the Small Δ portfolios are significantly different from zero. From the conditional sorting based on firm size, we can observe that this difference becomes economically and statistically insignificant for large firms (tercile 3). While the average differences for small (tercile 1) and medium firms (tercile 2) amount to 2.97% and 4.79%, respectively, the average difference for large firms adds up to only 0.57%. A similar pattern persists for average abnormal share volume and the average abnormal turnover rate. Presorting stocks based on their value for Amihud's (2002) illiquidity ratio shows that the relationship between local search volume and abnormal dollar volume is statistically insignificant among the more liquid stocks in the sample (tercile 1). The differences in means between the Large Δ portfolios and the Small Δ portfolios equal 0.76% for the most liquid stocks (tercile 1), compared to 5.47% (tercile 2) and 2.73% (tercile 3) for the less liquid stocks.

Looking at Panel A of Table 5 instead, the results of the double-sorted portfolios generally support the previous finding that there does not seem to be a significant effect of local Google search volume on next month stock returns. While the average return differential between the Large Δ and the Small Δ portfolios is mostly negative for all four conditional sorts, it continues to be statistically insignificant in all but one case.

Table 4
Double-sorted portfolios: Abnormal dollar volume

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
			Panel A: Local Google search volume			
By Size						
1	−0.36	−0.75	2.61	2.97*	−0.28	6.22
2	−0.73	0.51	4.06	4.79***	2.28	7.31
3	0.34	0.84	0.91	0.57	−1.07	2.20
By Book-to-Market						
1	−0.06	0.46	4.32	4.38***	1.92	6.83
2	−0.14	0.28	2.06	2.20*	−0.27	4.67
3	−0.89	−0.73	2.13	3.02**	0.20	5.83
By Current Month Return						
1	−0.57	0.11	1.80	2.37**	0.21	4.53
2	−4.83	−4.10	−3.23	1.60	−0.55	3.76
3	4.43	3.07	7.25	2.82**	0.19	5.46
By Amihud's (2002) Illiquidity Ratio						
1	1.80	2.21	2.56	0.76	−0.84	2.36
2	0.10	1.05	5.57	5.47***	2.79	8.13
3	−2.43	−4.07	0.30	2.73*	−0.43	5.91
			Panel B: Global Google search volume			
By Size						
1	−1.26	−1.76	5.07	6.33***	2.56	10.10
2	0.52	0.17	3.20	2.68**	0.36	5.00
3	−0.11	0.77	1.42	1.53*	−0.10	3.16
By Book-to-Market						
1	0.14	0.87	3.74	3.60***	1.28	5.93
2	0.23	−0.68	3.34	3.11**	0.38	5.84
3	−0.88	−1.32	2.53	3.41**	0.22	6.61
By Current Month Return						
1	−1.20	−0.93	2.44	3.64***	1.56	5.73
2	−4.12	−4.09	−3.92	0.20	−1.81	2.21
3	4.86	3.12	6.59	1.73	−0.87	4.32
By Amihud's (2002) Illiquidity Ratio						
1	1.65	1.60	2.97	1.32	−0.27	2.92
2	0.82	1.16	6.00	5.18***	2.50	7.86
3	−2.54	−5.82	1.92	4.46**	0.81	8.11

This table depicts the average contemporaneous abnormal dollar volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Abnormal dollar volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5
Double-sorted portfolios: Next month returns

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	2.22	2.09	1.75	−0.47	−1.16	0.21
2	1.19	1.40	1.41	0.22	−0.38	0.82
3	1.07	0.86	0.80	−0.27	−0.82	0.28
By Book-to-Market						
1	1.32	1.27	1.29	−0.03	−0.61	0.55
2	1.62	1.49	1.37	−0.25	−0.87	0.37
3	1.59	1.48	1.40	−0.19	−0.87	0.48
By Current Month Return						
1	1.64	1.38	1.55	−0.09	−0.74	0.56
2	1.65	1.39	1.32	−0.33	−0.92	0.26
3	1.40	1.36	1.07	−0.33	−0.95	0.30
By Amihud's (2002) Illiquidity Ratio						
1	1.21	1.00	0.89	−0.32	−0.88	0.24
2	1.12	1.27	1.35	0.23	−0.38	0.85
3	2.37	1.95	1.73	−0.64*	−1.31	0.04
Panel B: Global Google search volume						
By Size						
1	1.88	2.36	2.32	0.44	−0.21	1.10
2	1.30	1.62	1.14	−0.16	−0.75	0.42
3	0.82	0.84	1.12	0.30	−0.22	0.82
By Book-to-Market						
1	1.16	1.12	1.55	0.39	−0.16	0.93
2	1.50	1.57	1.81	0.31	−0.29	0.90
3	1.41	1.79	1.52	0.11	−0.52	0.74
By Current Month Return						
1	1.45	1.74	1.68	0.23	−0.39	0.86
2	1.57	1.24	1.71	0.14	−0.43	0.70
3	1.10	1.45	1.42	0.32	−0.28	0.91
By Amihud's (2002) Illiquidity Ratio						
1	1.08	0.97	1.04	−0.04	−0.57	0.49
2	1.11	1.51	1.39	0.28	−0.32	0.88
3	1.93	2.30	2.17	0.24	−0.41	0.88

This table depicts average next month returns of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Returns are given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Global Google Search Volume

In the case of global Google search volume, the positive contemporaneous relationship between Google search intensity and abnormal dollar volume and is still present when controlling for multiple firm characteristics one at a time, as can be seen in Panel B of Table 4. The average differences in abnormal dollar volume between stocks that display large signed changes and stocks that display small signed changes in global search volume are always positive and in most cases also statistically significant. When stocks are presorted based on firm size, the average difference in abnormal dollar volume becomes economically and statistically less significant for larger firms (tercile 3). The difference in means for large firms amounts to 1.53% compared to 6.33% and 2.68% for small (tercile 1) and medium-sized (tercile 2) firms, respectively. Similarly, the average difference in abnormal dollar volume becomes statistically insignificant for stocks that display a lower illiquidity ratio (tercile 1). The presorted portfolios based on current month return further indicate that a significant relationship between global search volume and abnormal dollar volume is only found among low current return (i.e., loser) stocks (tercile 1).

For global Google search volume and its effect on next month stock returns, the double-sorted portfolios do not support the previous result that stocks with large signed changes in global search volume earn on average higher expected returns than stocks with small signed changes in global search volume. The results in Panel B of Table 5 show that the difference in means becomes negative for medium-sized firms (tercile 2) and the most liquid stocks (tercile 1) and is further statistically insignificant for all investigated subportfolios.

Analysis of Double-sorted Portfolios

Portfolios of stocks with large signed changes in Google search volume exhibit, on average, a higher contemporaneous abnormal trading activity than portfolios of stocks with small signed changes in Google search volume. This pattern persists even when controlling for firm size, book-to-market value, current month return, and stock illiquidity one at a time. Moreover, it can be observed for both local and global search volume. When controlling for firm size, the average difference in abnormal dollar volume becomes economically and statistically less significant for stocks with larger market capitalizations. The relationship between Google search volume and traded dollar volume therefore seems to be particularly strong for small and medium capitalization stocks as opposed to large capitalization stocks. Lee et al. (1991), for example, suggest that small individual investors usually concentrate their investment holdings in small-capitalization stocks. As Google search volume most likely captures the attention from primarily this group of investors (e.g., Da et al., 2011; Vozlyublennaia, 2013), its effect on contemporaneous trading activity may be more pronounced in the small capitalization segment of the Nordic stock market. Moreover, the univariate portfolio sorts showed that it is the smaller firms in the sample that experience on average large signed changes in their Google search volume, which further supports this argument. However, since the differences in means between the Large Δ and the Small Δ portfolios are always positive and mostly significant for all conditional sorts, the relationship between Google search volume and contemporaneous trading activity does not seem to originate from the market capitalization of stocks in the sample (see also Bank et al., 2011). Furthermore, the conditional sorts based on Amihud's (2002) illiquidity ratio show that the relationship is stronger among the more illiquid stocks in the sample. The similar results from conditioning on either firm size or stock illiquidity could originate from the interdependence between the two characteristics. Amihud (2002) finds that illiquidity effects tend to be stronger for stocks with smaller market capitalizations since larger stock issues have a smaller price impact for a given order flow. Thus, it is likely that the observations in the small- and medium firm size subportfolios are also included in the medium- and large illiquidity subportfolios

The results for next month returns from the double-sorted portfolios indicate that evidence for a significant effect of Google search volume on future stock returns in the sample seems rather weak. The average return differential between the Large Δ and Small Δ subportfolios continues to be mostly negative, albeit statistically insignificant, when employing local search volume. In the case of global search volume, the double-sorted portfolios do not support the finding that there is a significant positive return differential between stocks with large signed changes and stocks with small signed changes in global search volume. One potential explanation for the insignificant return differentials in the case of global search volume could be the small sample size. With an average size of nine to twelve stocks, the various subportfolios have only few stocks in them. Therefore, they are more prone to outliers, which could cause distortions in average portfolio characteristics, such as next month returns. Furthermore, the relatively wide 95% confidence intervals imply larger standard errors and consequently less precise estimates of the difference in mean returns between the Large Δ and Small Δ portfolios.

5.3 Factor Model Regressions

Based on the different results for local and global search volume, two separate zero-investment strategies are formed, for which stocks are sorted according to their signed changes in Google search volume, $\Delta GSV^{i}_{r,\,t}$. The time-series of next month returns for the zero-cost portfolios is then regressed on various risk factors constructed for the Nordic market. Table 6 reports the baseline results when local Google search volume is employed. Results for the strategy based on global Google search volume are depicted in Table 7.

Local Google Search Volume

Panel A of Table 6 presents the mean and the multivariate regression results for a zero-investment strategy that goes long in stocks with small signed changes in local search volume and short in stocks with large signed changes in local search volume. The first column labeled "Mean" shows that the next month return of the long leg is on average 0.19 percentage points higher than the return of the short leg. The intercepts in the CAPM and the Fama-French (1993) three-factor model are with 0.18 and 0.17 both positive, albeit not statistically significant. The results for the Carhart (1997) four-factor model are somewhat puzzling considering the insignificant alpha estimates for the other two factor models. Instead, the intercept in this model equals 0.48 and is statistically significant at the 1% level. The exposure of the zero-investment strategy can be examined via the risk factors loadings. For the Carhart (1997) four-factor model, the negative and significant coefficient on WML shows that the strategy has a negative exposure to momentum stocks, which is mainly driven by its long position. As can be seen in Table 3, stocks with small signed changes in local search volume significantly co-move with previous loser stocks. The factor

Table 6
Factor models: Local Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
	Panel A: Coefficients for long-short strategy			
$MKT-RF$	-	0.0105	0.0053	-0.0356
		(0.0269)	(0.0274)	(0.0274)
SMB	-	-	-0.0266	-0.0669
			(0.0781)	(0.0746)
HML	-	-	0.1047	0.0546
			(0.0802)	(0.0768)
WML	-	-	-	-0.2472^{***}
				(0.0526)
$Intercept$	0.1887	0.1801	0.1732	0.4812^{***}
	(0.1615)	(0.1634)	(0.1639)	(0.1686)
Observations	190	190	190	190
R^2		0.0008	0.0103	0.1157
	Panel B: Alphas for $Small$ Δ stocks (Long)			
$Intercept$	1.4299^{***}	0.6060^{***}	0.6138^{***}	0.9119^{***}
	(0.4601)	(0.1335)	(0.1330)	(0.1333)
	Panel C: Alphas for $Large$ Δ stocks (Short)			
$Intercept$	1.2411^{***}	0.4259^{***}	0.4406^{***}	0.4307^{***}
	(0.4553)	(0.1323)	(0.1324)	(0.1441)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with small signed changes in local Google search volume and short in a portfolio of stocks with large signed changes in local Google search volume. The portfolios are formed each month by sorting stocks into three quantiles of equal size according to their signed changes in local search volume. The equal-weighted average returns of this strategy in the month following portfolio formation are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. $MKT-RF$ denotes a portfolio's exposure to the market factor, SMB its exposure to the size factor, HML its exposure to the value factor, and WML its exposure to the momentum factor. Panel B and C show intercepts from the regressions of excess returns (i.e., portfolio return minus one-month U.S. T-Bill rate) on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

loadings on $MKT-RF$, SMB, and HML, on the other hand, are not significantly different from zero.

Panels B and C of Table 6 separately investigate the long and short position of the zero-cost portfolio. For both long- and short leg, the alphas are always positive and statistically significant at the 1% level, yet different in magnitude.

Global Google Search Volume

Panel A of Table 7 displays the mean and the multivariate regression results for a zero-investment strategy that goes long in stocks with large signed changes in global search volume and short in stocks with small signed changes in global search

Table 7
Factor models: Global Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
Panel A: Coefficients for long-short strategy				
$MKT-RF$	-	0.0102	0.01094	0.0064
		(0.0227)	(0.0232)	(0.0245)
SMB	-	-	-0.0142	-0.0186
			(0.0662)	(0.0668)
HML	-	-	-0.0372	-0.0427
			(0.0680)	(0.0688)
WML	-	-	-	-0.0273
				(0.0471)
Intercept	0.3087**	0.3003**	0.2993**	0.3333**
	(0.1363)	(0.1379)	(0.1388)	(0.1510)
Observations	190	190	190	190
R^2		0.0012	0.0030	0.0048
Panel B: Alphas for *Large* Δ stocks (Long)				
Intercept	1.5889***	0.7637***	0.7771***	0.8870***
	(0.4555)	(0.1135)	(0.1127)	(0.1209)
Panel C: Alphas for *Small* Δ stocks (Short)				
Intercept	1.2803***	0.4634***	0.4779***	0.5536***
	(0.4539)	(0.1240)	(0.1225)	(0.1326)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with large signed changes in global Google search volume and short in a portfolio of stocks with small signed changes in global Google search volume. The portfolios are formed each month by sorting stocks into three quantiles of equal size according to their signed changes in global search volume. The equal-weighted average returns of this strategy in the month following portfolio formation are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. $MKT-RF$ denotes a portfolio's exposure to the market factor, SMB its exposure to the size factor, HML its exposure to the value factor, and WML its exposure to the momentum factor. Panel B and C show intercepts from the regressions of excess returns (i.e., portfolio return minus one-month U.S. T-Bill rate) on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

volume. The next month return of the long position is on average 0.31 percentage points higher than the next month return of the short position. Furthermore, the intercepts in the CAPM, the Fama-French three-factor (1993) model, and the Carhart (1997) four-factor model are all positive and amount to 0.30, 0.30 and 0.33, respectively. For all three proposed factor models, the alphas are statistically significant at the 5% level. Contrary to the proposed strategy based on local search volume, this strategy does not have a significant exposure to the momentum factor. In addition, the factor loadings on $MKT-RF$, SMB, and HML are all statistically insignificant.

Estimated alphas for the excess returns of the long and short position are separately displayed in Panel B and C of Table 7. As both the long- and short leg of the zero-investment strategy display positive and significant alphas, it is the difference in alphas between the Large Δ stocks and the Small Δ stocks that drives the results.

Analysis of Factor Models

For the zero-investment strategy based on local Google search volume, the intercepts in the CAPM and the Fama-French (1993) three-factor model are not significantly different from zero, suggesting that the trading strategy does not earn significant abnormal returns, which cannot be explained by other risk factors. This result would further reinforce previous findings from the single- and double sorted portfolios that local Google search volume cannot predict future stock returns in the sample. For the Carhart (1997) four-factor model, however, the alpha estimate is now economically and statistically significant. There are several potential explanations for this outcome. First, this finding could be related to the statistical properties of the OLS estimators. In particular, in the presence of multicollinearity between the explanatory variables (i.e., the risk factors), the true variance of the estimated parameters is quite large. As a consequence, coefficients tend to be unstable across different samples and sensitive to even small changes in the model, such as adding additional regressors (Bello, 2008). Following Sakowski et al. (2016), the variance inflation factor is calculated for the individual coefficients in order to detect potential multicollinearity issues.[9] However, the results for the test statistic are with 1.03 - 1.15 well below the cutoff value of 10, above which multicollinearity is often deemed a problem. A second explanation could be the Small Δ portfolio's significant negative exposure to momentum stocks. As the Small Δ portfolio, and subsequently also the zero-investment strategy that goes long in it, may have a low loading on the momentum factor, it receives a negative coefficient on the related factor mimicking portfolio. Since the zero-investment strategy still earns positive returns on average, the intercept is positive and becomes statistically significant (Asgharian & Hansson, 2005). Last but not least, the potential interaction effect with momentum exposure seems to be concentrated around the 2008-2009 global financial crisis period. When testing the Carhart (1997) four-factor model for different sample periods, the effect

[9] A derivation of the variance inflation factor and the corresponding results are presented under Appendix B.

disappears for those that exclude the financial crisis. A phenomenon that was particularly observable during this period are so-called ”momentum crashes”. They occur in panic states when market volatility is high and lead to portfolios consisting of past-loser stocks notably outperforming portfolios with past-winner stocks (Daniel & Moskowitz, 2016). Based on these explanations, the parameter estimates for the Carhart (1997) four-factor model may not provide any analyzable information in this case.

For the second strategy based on global Google search volume, the intercepts are positive and statistically significant at the 5% level for all three factor model specifications. This finding is in line with Bank et al. (2011), who report alpha estimates of similar magnitude for their strategy of going long in stocks with large signed changes in search volume and short in stocks with small signed changes in search volume. The results for the strategy based on global search volume point towards an attention induced risk premium, which cannot be explained by other risk factors for the Nordic market. According to Fang & Peress (2009), the observation that both long- and short position of this strategy display positive alphas reflects the equal-weighting approach used to calculate portfolio returns and the small number of stocks in the sample. The fact that alphas are higher for the Large Δ portfolio, however, indicates that the negative effect of investor recognition on next month stock returns, which is predicted by Merton (1987), is not present in the data.

Finally, looking at the R^2, the overall fit for all three factor models is rather weak. While Fama and French (2012) find that local three- and four-factor models using local explanatory returns can help explain local average returns for portfolios formed on size and value versus growth, they also acknowledge that the factor models may have less success with portfolios formed in other ways, as is the case here.

5.4 Robustness Tests

The next section introduces several robustness tests on the baseline results presented in Tables 2 to 7. In particular, an alternative measure of Google search intensity is introduced, stocks are further sorted based on a combined score incorporating both local and global Google search volume, and weekly, instead of monthly rebalancing of portfolios is investigated.

Alternative Measure of Google Search Intensity

To address concerns that study results are driven by the choice of search intensity measure, the robustness of previous results is tested by calculating and applying abnormal Google search volume. It is defined as a stock's Google search volume in the current period minus the median value of Google search volume in the previous twelve periods[10]:

$$AGSV_{r,\ t}^{i} = GSV_{r,\ t}^{i} - Med(GSV_{r,\ t-1}^{i}, \ldots, GSV_{r,\ t-12}^{i}) \tag{14}$$

where $AGSV_{r,\ t}^{i}$ denotes firm i's abnormal Google search volume in region r and time period t. This approach is roughly based on a study by Da et al. (2011), who introduce a similar measure of abnormal weekly Google search volume. They argue that the median over a longer time period can better capture the "normal" attention level and is robust to more recent jumps in Google search volume. The method further removes time trends and other low frequency seasonalities, which could otherwise drive the results. A higher abnormal Google search volume in one period is thus linked to an increase in Internet search intensity and subsequently investor attention.

Each month, all stocks in the sample are sorted according to their value of abnormal Google search volume, $AGSV_{r,\ t}^{i}$. Local and global Google search volume is again employed individually, and outcomes are compared. The corresponding results for the single- and double-sorted portfolios, as well as the factor model regressions are presented in Tables D1-D8 under Appendix D.

The positive effect of increased Internet search intensity on contemporaneous trading activity is still present when sorting stocks based on their abnormal Google search volume. Focusing solely on local search queries, the differences in means for abnormal share volume, abnormal dollar volume, and the abnormal turnover rate between stocks with high abnormal search volume and stocks with low abnormal search volume are 4.73%, 4.80%, and 5.14%, respectively. The corresponding differences in means for the three variables when employing global search volume are 5.24%, 5.18%, and 5.66%. These differences are all statistically significant at the

[10] The main results are robust to the choice of rolling window length (3, 4, 6, and 8 periods).

1% level and slightly greater in magnitude compared to the baseline results, which range between 2.92-3.92%. The double-sorted portfolios controlling for firm size, book-to-market value, current month return, and stock illiquidity all support the unconditional results for both local and global search volume. As is the case for the initial sorts based on signed changes in Google search volume, the positive relationship between abnormal Google search volume and contemporaneous trading activity seems to be particularly strong for firms with a small market capitalization.

Evidence for a significant effect of Google search volume on next month stock returns is weak when employing a stock's abnormal Google search volume as a measure of search intensity. When stocks are sorted based on local search volume, stocks with low abnormal search volume earn on average a statistically insignificant higher return than stocks with high abnormal search volume. For global search volume, the average return differential between stocks with high abnormal search volume and stocks with low abnormal search volume is positive, albeit not significantly different from zero. These patterns can be observed for the single- as well as the double-sorted portfolios. In addition, the intercepts in the factor model regressions are statistically insignificant for both proposed trading strategies. The only exception is again the intercept in the Carhart (1997) four-factor model for the zero-investment strategy based on local search volume.

In general, the relationship between the variation in a stock's Google search volume and its contemporaneous trading activity seems to be robust with regards to the two different investigated measures of search intensity. However, employing abnormal Google search volume cannot support the previous finding that stocks with high global search intensity (as measured by large signed changes in global search volume) earn significant abnormal returns, which cannot be explained by other known risk factors for the Nordic market.

Sorts Based on Combined Score

Table 8 gives an overview of the portfolio outcomes resulting from the two different sorts based on local or global Google search volume. The fields depict the proportions of valid firm-month observations that are assigned to each of the three terciles according to their local search volume (rows) while at the same time to either of the

Table 8
Portfolio sorts: Conditional proportions

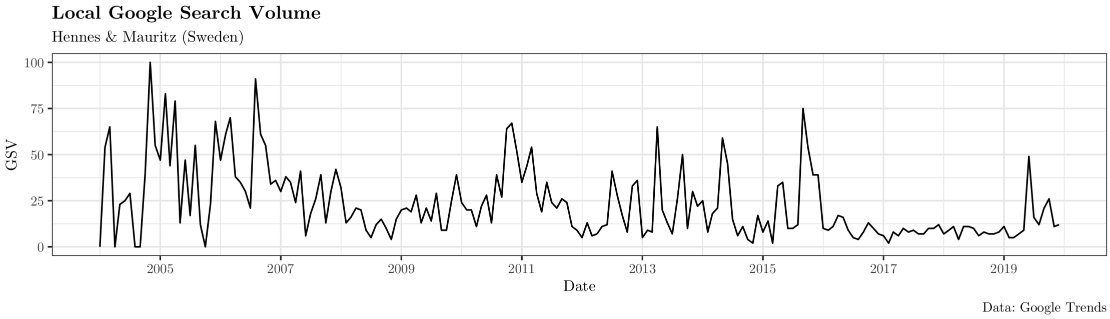
Local/Global	Small Δ	Medium Δ	Large Δ	Sum
Small Δ	15.93	10.16	7.59	33.68
Medium Δ	10.02	14.17	9.23	33.42
Large Δ	7.55	9.40	15.95	32.90
Sum	33.50	33.73	32.77	100.00

The table fields depict the proportions of valid firm-month observations that are assigned to each of the three terciles according to their local search volume while at the same time to either of the three terciles according to their global search volume. The field labeled (Small Δ, Small Δ), for example, gives the percentage of firm month observations that are assigned to the bottom tercile portfolio for both sorts. The rows relate to local search volume portfolios while the columns relate to global search volume portfolios. The proportions are given in %.

three terciles according to their global search volume (columns). The values on the diagonal thus represent the percentages of valid firm-month observations that end up in the Small Δ, Medium Δ, and Large Δ portfolio, irrespective of whether local search volume or global search volume is employed. If both sorts always led to the same portfolio compositions, all three values would approximately equal 1/3 since stocks are sorted into terciles. A value of 15.93% for the Small Δ portfolios implies that only around 48% of observations that are in the bottom tercile when sorting is based on local search volume are also in the bottom tercile when sorting is based on global search volume. Similarly, for the Large Δ portfolios, a value of 15.95% implies that only around 48% of observations that are in the top tercile for sorts based on local search volume are also in the top tercile for sorts based on global search volume.

Figure 2 plots the monthly local and global Google search volume for the search term "Hennes & Mauritz" from January 2004 to December 2019. We can see that the time series of global search volume data appears to be much less volatile than the time series of local search volume data. Consequently, the stock may be more likely to get assigned to the Large Δ portfolio when sorting is based on local search volume as opposed to global search volume. The difference between local and global search volume is particularly notable in the period between 2009 and 2017.

Since the disparity between portfolio compositions for local and global search volume is rather high, sorting based on a combined score for the two is further investigated. Each month, all stocks that display a valid observation for both local and global Google search volume are first sorted into terciles and given a rank (i.e., from



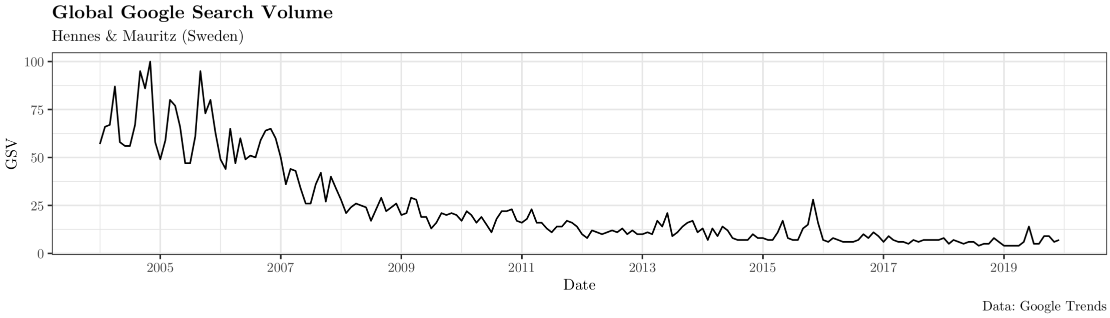


Figure 2: **Illustration of local versus global Google search volume**

This figure plots the monthly local and global Google search volume for a sample stock between January 2004 and December 2019. The search term is "Hennes & Mauritz". GSV stands for Google search volume and represents the raw data published by Google Trends.

1 to 3) according to their signed changes in local search volume. Next, all stocks are again sorted into terciles and given a rank (i.e., from 1 to 3) based on their signed changes in global search volume. The two scores are added up and stocks are sorted and assigned to one of the three portfolios based on their cumulative rank (i.e. from 2 to 6). To some extent, this score now reflects the direction and size of change in a stock's local and global Google search volume combined. The corresponding results for the single- and double-sorted portfolios are presented in Tables E1-E6 under Appendix E.

The positive relationship between Google search volume and contemporaneous trading activity is still present when stocks are sorted according to a combined score of local and global search volume. For abnormal dollar volume, abnormal share volume, and the abnormal turnover rate, the differences in means between stocks in the Large Δ portfolio and stocks in the Small Δ portfolio are statistically significant at the 1% level. On average, stocks with large signed changes in combined search volume report an abnormal share volume that is 3.74 percentage points higher per month than the abnormal share volume of stocks with small signed changes in com-

Table 9
Factor models: Combined Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
	Panel A: Coefficients for long-short strategy			
$MKT-RF$	-	-0.0206	-0.0163	0.0112
		(0.0243)	(0.0247)	(0.0254)
SMB	-	-	0.0284	0.0555
			(0.0706)	(0.0691)
HML	-	-	-0.0797	-0.0460
			(0.0724)	(0.0711)
WML	-	-	-	0.1662***
				(0.0488)
$Intercept$	0.1237	0.1406	0.1471	-0.0600
	(0.1459)	(0.1473)	(0.1480)	(0.1562)
Observations	190	190	190	190
R^2		0.0038	0.0109	0.0693
	Panel B: Alphas for *Large* Δ stocks (Long)			
$Intercept$	1.4804***	0.6707***	0.6814***	0.7032***
	(0.4500)	(0.1233)	(0.1234)	(0.1343)
	Panel C: Alphas for *Small* Δ stocks (Short)			
$Intercept$	1.3566***	0.5301***	0.5343***	0.7632***
	(0.4588)	(0.1238)	(0.1232)	(0.1270)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with large signed changes in combined Google search volume and short in a portfolio of stocks with small signed changes in combined Google search volume. Each month, stocks are first sorted and given a rank according to their signed changes in local search volume. Next, stocks are sorted again and given a rank according to their signed changes in global search volume. The two scores are added up and stocks are sorted and assigned to portfolios based on their cumulative rank. The equal-weighted average returns of this strategy in the month following portfolio formation are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. $MKT-RF$ denotes a portfolio's exposure to the market factor, SMB its exposure to the size factor, HML its exposure to the value factor, and WML its exposure to the momentum factor. Panel B and C show intercepts from the regressions of monthly excess returns (i.e., portfolio return minus one-month U.S. T-Bill rate) on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

bined search volume. Moreover, such stocks have a dollar volume that is on average 3.63 percentage points higher and a turnover rate that is on average 4.13 percentage points higher per month. The double-sorts controlling for firm size, book-to-market value, current month return, and stock illiquidity further support these findings. Based on the unconditional sorts, stocks with large signed changes in combined search volume earn on average slightly higher returns than stocks with small signed changes in combined search volume. However, this average return differential is not significantly different from zero. For the double-sorted portfolios, the differences in mean returns between the Large Δ and Small Δ portfolios are either positive or negative, albeit also statistically insignificant for all subportfolios.

Table 9 presents the mean and the multivariate regression results for a zero-investment strategy that goes long in stocks with large signed changes in combined Google search volume and short in stocks with small signed changes in combined Google search volume. While the alphas are positive for the CAPM and the Fama-French (1993) three-factor model, the intercept becomes negative for the Carhart (1997) four-factor model. For all three factor models, however, the alpha estimates are not significantly different from zero.

To conclude, the positive and significant relationship between Google search volume and contemporaneous trading activity is still present when stocks are sorted according to a combined score for local and global search volume. The results for next month portfolio returns, on the other hand, further indicate that there does not seem to be a significant effect of Google search volume on next month stock returns in the sample.

Weekly Portfolio Formation

Most previous research that employs Google search volume to study its effect on stock market movements uses weekly observations from Google Trends (e.g., Da et al., 2011; Joseph et al., 2011; Vlastakis & Markellos, 2012). Weekly variation in a stock's Google search volume may capture increased search intensity and consequently investor attention in a timelier fashion than monthly variation. Barber and Odean (2001), for example, claim that individual investors nowadays check their stock positions several times a day on the Internet compared to once a day in the morning paper like a decade ago. As a result, a bigger proportion of investors pay attention to short-term return trends than ever before. Google Trends only reports weekly observations for Google search volume for a time range of up to five years, which significantly decreases the time-series dimension of the data set. Therefore, monthly observations are employed in the main analysis of this study. However, to test the robustness of the previous results, the effect of Google search volume on trading activity and stock returns in the Nordics is further investigated by using weekly observations for local and global Google search volume.

With regards to the employed trading activity measures, the daily values for share volume, dollar volume, and the turnover rate are summed up to match the weekly frequency of the Google Trends data. For Amihud's (2002) illiquidity ratio, weekly averages are calculated. Abnormal trading activity is further computed by taking the share volume, dollar volume, turnover rate, and illiquidity ratio in a given week and subtracting the respective averages over the entire calendar year. At the beginning of each week, all stocks are sorted according to their signed changes in Google search volume and held in the portfolio for the entire trading week. Average abnormal trading activity and average returns in the week following portfolio formation are examined for the three resulting Google search volume portfolios. For the factor model analysis, a zero-investment strategy is constructed that goes long in stocks with large signed changes in weekly search volume and short in stocks with small signed changes in weekly search volume. Following Joseph et al. (2001), the daily returns for the zero-cost portfolio are subsequently regressed on the proposed risk factors. Since the data set provided by AQR Capital Management only includes monthly factor data for the Nordic countries, daily factors for the European market published on Kenneth R. French's website are employed instead. The corresponding results for the single- and double-sorted portfolios, as well as the factor model regressions are presented in Tables F1-F7 under Appendix F.

Table 10 reports both average contemporaneous abnormal trading activity as well as average abnormal trading activity in the week following portfolio formation. Looking at the first three rows of Panel A and B, there does not seem to be a contemporaneous relationship between weekly Google search volume and trading activity in the sample. The differences in means for abnormal share volume, abnormal dollar volume, and the abnormal turnover rate between stocks in the Large **Δ** portfolio and stocks in the Small **Δ** portfolio are all negative, albeit not significantly different from zero. Tabulating the values for the week following portfolio formation instead shows that these differences become positive and statistically significant at the 1% level. This pattern persists for both local and global Google search volume. The conditional sorts on firm size, book-to-market value, current month return, and stock illiquidity generally support the finding that an increase in weekly Google search volume leads to higher abnormal trading activity in the week following portfolio formation. Similar to the findings for monthly portfolio formation, an increase

Table 10
Weekly single-sorted portfolios: Abnormal trading activity

	Δ Search Volume			Difference	95% CI	
Variable	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
AVO_t	3.42	0.11	2.50	−0.92	−2.67	0.83
$\$AVO_t$	3.40	0.31	2.68	−0.72	−2.48	1.03
ATO_t	2.79	−0.22	1.92	−0.87	−2.65	0.93
$AILLIQ_t$	−1.89	0.12	−0.45	1.44*	−0.01	2.89
AVO_{t+1}	−0.78	−1.41	3.14	3.92***	2.31	5.54
$\$AVO_{t+1}$	−0.73	−1.07	3.31	4.04***	2.44	5.65
ATO_{t+1}	−1.48	−1.76	2.60	4.08***	2.42	5.74
$AILLIQ_{t+1}$	−1.06	−0.44	−1.22	−0.16	−1.62	1.29
Panel B: Global Google search volume						
AVO_t	2.97	0.99	1.61	−1.37	−3.11	0.38
$\$AVO_t$	3.14	0.85	1.86	−1.28	−3.02	0.47
ATO_t	2.39	0.67	1.07	−1.31	−3.09	0.47
$AILLIQ_t$	−0.93	−0.51	−0.37	0.55	−0.79	1.90
AVO_{t+1}	−1.50	−0.89	2.43	3.92***	2.27	5.58
$\$AVO_{t+1}$	−1.25	−0.92	2.71	3.96***	2.32	5.61
ATO_{t+1}	−2.13	−1.23	1.90	4.04***	2.34	5.74
$AILLIQ_{t+1}$	−0.78	−0.85	−0.63	0.15	−1.22	1.53

This table depicts average abnormal trading activity of weekly portfolios, which consist of stocks sorted according to their signed changes in Google search volume. AVO_t is the contemporaneous abnormal share volume, $\$AVO_t$ the contemporaneous abnormal dollar volume, ATO_t the contemporaneous abnormal turnover rate, and $AILLIQ_t$ the contemporaneous abnormal illiquidity ratio in %. AVO_{t+1} is the following week abnormal share volume, $\$AVO_{t+1}$ the following week abnormal dollar volume, ATO_{t+1} the following week abnormal turnover rate, and $AILLIQ_t$ the following week abnormal illiquidity ratio in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

in Google search volume does not induce improved stock liquidity as measured by Amihud's (2002) illiquidity ratio. In fact, stocks with small signed changes in local search volume report a larger contemporaneous decrease in weekly stock illiquidity than stocks with large signed changes in local search volume, which is significant at the 10% level.

Further, there is no significant effect of Google search volume on next week stock returns present in the data. Employing both local and global search volume, the average return differential between stocks with large signed changes and stocks with small signed changes in weekly search volume is positive in both cases, but not significantly different from zero. The double-sorted portfolios further show similar results.

Moreover, when regressing the daily zero-cost portfolio returns on the proposed risk factors for the European market, the alphas for the respective model specifications are all positive albeit not statistically significant.

With regards to weekly Google search volume and its effect on trading activity, there does not seem to be a pronounced contemporaneous relationship in the data. However, there is a significant positive effect of a stock's weekly change in Google search volume on abnormal dollar volume, abnormal share volume, and the abnormal turnover rate in the week following portfolio formation. This finding is in line with Da et al. (2011), who suggest that Google search volume is a lead indicator for trading activity since investors may only trade after paying attention to a stock. Furthermore, the results for average next week returns as well as abnormal daily returns indicate there does not seem to be a significant return premium associated with stocks that display large signed changes in weekly Google search volume as opposed to stocks that display small signed changes in weekly Google search volume.

5.5 Study Limitations

The study on Google search volume and its influence on returns and trading activity in Nordic stock markets comes with certain limitations. First, previous research using Google Trends data suggests employing stock tickers instead of company names as keywords (e.g., Da et al., 2011; Joseph et al., 2011). Search queries for company names can yield a range of information that are unrelated to investment decisions, such as product information as well as store locations or hours. Moreover, investors may use several different variations of a company name when searching for a firm. Last but not least, companies sometimes undergo name changes after mergers and acquisitions, which could make the use of firm names as search terms even more challenging. Search queries based on stock tickers, on the other hand, are less ambiguous according to Da et al. (2011). For example, if Internet users are searching for "SWMA", it is more likely that they are interested in financial information about the stock of Swedish Match AB instead of information about the company's tobacco products. Since stock tickers are always uniquely assigned, using them also mitigates the issue of multiple reference names. Joseph et al. (2011) further claim that the effort required to process the results of a stock ticker search is only worthwhile for investors who are seriously considering an investment decision. In theory, focusing on stock tickers instead of firm names would certainly be desirable in this study. However, Google Trends does not return valid data for several stock tickers in the sample as not enough search queries were submitted in the time period and region specified. Removing these stocks from the sample would then consequently lead to a bias towards larger and better known stocks.

Second, the Google search volume employed may not adequately proxy for attention from the overall Nordic market investor base. In general, most previous research related to the topic focuses only on the U.S. market and subsequently employs search queries submitted by U.S. Internet users. Bijl et al. (2016) reason that investors normally prefer to trade on their domestic market, which is why the population of U.S. Internet users should contain a bigger proportion of U.S. market investors than the worldwide population of Internet users does. They further report that trading strategies based on local search volume are more successful than strategies based on global search volume. This study, on the other hand, focuses on an entire region with a sample of stocks from four different countries. Employing local Google search volume may thus neglect attention from investors situated within that region, but outside of the country in which a particular stock is listed on an exchange. Alternatively, global Google search volume may capture attention from an investor base that is too broad and subsequently contains a lot of noise. Since Google Trends does not yet provide aggregated search volume data for multiple countries combined, these constraints have to ultimately be weighted against each other.

Third, the results and inferences may be subject to look-ahead bias and survivorship bias. Look-ahead bias occurs when a study is based on data that was not yet available or known during the time period examined. In particular, when back testing a trading strategy that depends on external signals, such as a stock's Google search volume, it is critical to first determine whether this signal was already available at the dates it includes. The nature of Google Trends data introduces this bias since the website does not publish the absolute number of submitted search queries, but a scaled value so that for each keyword, the time period with the highest relative search volume observed gets assigned a value of 100. However, back when this particularly high search volume was recorded, it was not yet evident for investors that it would become the highest search volume observed during the time period examined. This issue is partly mitigated by comparing changes in monthly Google search volume rather than simply employing the raw data. Survivorship bias, on the other hand, arises as only stocks currently listed on the NASDAQ OMX Nordic 120 are studied. Therefore, only the "surviving" stocks that were large enough to still be included in the index at the end of the observation period are considered, which could lead to a distortion of portfolio performance characteristics. Consequently, the study should be extended to include historical index composition and consider all stocks that were included in the index during the sampling period from January 2004 to December 2019 (see also Da et. al, 2011).

Lastly, the study's small simple size and short sample period pose additional challenges. When using portfolio sorts in asset pricing research, a small sample size could lead to distortions in average performance characteristics as the individual portfolios only contain very few stocks. Moreover, it prevents the analysis of different portfolio sizes (i.e., sorting stocks into quartiles, quintiles, etc.) to ensure that results are robust to the choice of portfolio size. Stocks listed on the NASDAQ OMX Nordic 120 are chosen to make the task of examining all search queries and individually downloading them manageable. However, future research could expand the sample to include all stocks traded on the Nordic stock markets. The sample period is limited due to Google Trends only publishing search volume data starting from 2004. A longer sample period would enhance the ability to find significant factors influencing returns (Easley et al., 2002). As a result, the limited sample period certainly imposes a constraint on the testing approach.

6 Conclusion

This paper examines the relationship between Google search volume, returns, and trading activity in the Nordic stock markets. Google search queries on company names are hereby employed as a proxy to investigate whether investor attention has a significant effect on contemporaneous trading activity and expected stock returns in the Nordics. Local search queries from the country of stock market listing as well as worldwide search queries are considered individually, and the results are subsequently compared. Moreover, an approach to combine and jointly consider local and global Google search volume is suggested. Google search volume as an attention indicator is applied to all stocks currently listed on the NASDAQ OMX Nordic 120 index and the monthly observations span the period between January 2004 and December 2019.

First, the relationship between Google search volume and monthly trading activity is explored in order to examine how well variations in search intensity can capture attention from individual investors in the Nordic stock markets. By employing three different measures of abnormal trading activity, this study finds a significant contemporaneous relationship. Specifically, an increase in a stock's Google search volume is associated with higher abnormal share volume, higher abnormal dollar volume, and a higher abnormal turnover rate in a given month. This link seems to be particularly strong among the smaller and more illiquid stocks in the sample. However, a significant effect of Google search volume on stock liquidity, as measured by Amihud's (2002) illiquidity ratio, is not present in the data. As several previous studies suggest that higher Internet search intensity is also associated with improved stock liquidity, this relationship should be explored in more detail for the Nordic stock markets. Ideas for future research are hereby to follow a more refined panel estimation approach and to employ several different measures of illiquidity.

Based on the results of this study, evidence for a significant effect of Google search volume on future returns in Nordic stock markets seems rather weak. The baseline results when global search volume is employed indicate that stocks with increased Internet search intensity may earn an attention-induced return premium, which cannot be explained by other risk factors for the Nordic market. However, this result is not robust to employing a second proposed measure of Google search intensity or to investigating weekly instead of monthly variation in Google search volume. Moreover, the insignificant results when local or combined search volume is applied further support the general conclusion that Google search volume cannot predict abnormal returns in this sample of Nordic stocks. Since the sample size is relatively small due to the limited scope of this study, the analysis should certainly be expanded in the future to include all stocks traded on the Nordic stock exchanges. In addition, the construction of a more sophisticated approach to simultaneously consider search queries from multiple different countries is left for future research.

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Appendix A

Table A1
Sample overview: Search queries

Official Company Name	Country of Listing	Employed Search Query
A. P. Møeller - Mærsk A	Denmark	Mærsk A
A. P. Møeller - Mærsk B	Denmark	Mærsk B
AAK	Sweden	AAK
ABB	Sweden	ABB
ÅF Pöyry B	Sweden	ÅF Pöyry
Aker BP	Norway	Aker BP
Alfa Laval	Sweden	Alfa Laval
Ambu	Denmark	Ambu
ASSA ABLOY B	Sweden	ASSA ABLOY
AstraZeneca	Sweden	AstraZeneca
Atlas Copco A	Sweden	Atlas Copco A
Atlas Copco B	Sweden	Atlas Copco B
Autoliv SDB	Sweden	Autoliv
Axfood AB	Sweden	Axfood
Bakkafrost	Norway	Bakkafrost
Boliden	Sweden	Boliden
Carlsberg B	Denmark	Carlsberg
Castellum	Sweden	Castellum
Chr. Hansen Holding	Denmark	Chr. Hansen Holding
Coloplast	Denmark	Coloplast
Danske Bank	Denmark	Danske Bank
Demant	Denmark	Demant
DNB	Norway	DNB
Dometic Group	Sweden	Dometic Group
DSV Panalpina	Denmark	DSV
Electrolux B	Sweden	Electrolux
Elekta B	Sweden	Elekta
Elisa Oyj	Finland	Elisa Oyj
Epiroc A	Sweden	Epiroc A
Epiroc B	Sweden	Epiroc B
EQT	Sweden	EQT
Equinor	Norway	Equinor
Ericsson B	Sweden	Ericsson
Essity B	Sweden	Essity
Evolution Gaming Group	Sweden	Evolution Gaming Group
Fabege	Sweden	Fabege
Fastighets Balder B	Sweden	Fastighets Balder
Fortum	Finland	Fortum
Genmab	Denmark	Genmab
Getinge B	Sweden	Getinge

Table A1
Sample overview: Search queries

Official Company Name	Country of Listing	Employed Search Query
Gjensidige Forsikring	Norway	Gjensidige Forsikring
GN Store Nord	Denmark	GN Store Nord
Hennes & Mauritz B	Sweden	Hennes & Mauritz
Hexagon B	Sweden	Hexagon AB
HEXPOL B	Sweden	HEXPOL
Holmen	Sweden	Holmen AB
Hufvudstaden A	Sweden	Hufvudstaden
Huhtamaki Oyj	Finland	Huhtamaki
Husqvarna B	Sweden	Husqvarna
ICA Gruppen	Sweden	ICA Gruppen
Industrivärden A	Sweden	Industrivärden A
Industrivärden C	Sweden	Industrivärden C
Indutrade	Sweden	Indutrade
Intrum	Sweden	Intrum
Investor A	Sweden	Investor A
Investor B	Sweden	Investor B
ISS	Denmark	ISS A/S
Jyske Bank	Norway	Jyske Bank
Kesko	Finland	Kesko
Kinnevik B	Sweden	Kinnevik
KONE Oyj	Finland	KONE
Konecranes	Finland	Konecranes
Latour B	Sweden	Latour
Lifco	Sweden	Lifco
Loomis B	Sweden	Loomis
Lundbeck	Denmark	Lundbeck
Lundbergföretagen B	Sweden	Lundbergföretagen
Lundin Petroleum	Sweden	Lundin Petroleum
Metso Oyj	Finland	Metso
Millicom Int. Cellular SDB	Sweden	Millicom
Mowi	Norway	Mowi
Neste Oyj	Finland	Neste Oyj
NIBE Industrier B	Sweden	NIBE Industrier
Nokia Oyj	Finland	Nokia
Nokian Renkaat	Finland	Nokian Renkaat
Nordea Bank	Sweden	Nordea Bank
Norsk Hydro	Norway	Norsk Hydro
Novo Nordisk B	Denmark	Novo Nordisk
Novozymes B	Denmark	Novozymes
Orion Oyj B	Finland	Orion Oyj
Orkla	Norway	Orkla
Ørsted	Denmark	Ørsted

Table A1
Sample overview: Search queries

Official Company Name	Country of Listing	Employed Search Query
Pandora	Denmark	Pandora
Peab B	Sweden	Peab
Royal Unibrew	Denmark	Royal Unibrew
SAAB B	Sweden	SAAB
Salmar	Norway	Salmar
Sampo Oyj A	Finland	Sampo Oyj
Sandvik	Sweden	Sandvik
SCA B	Sweden	SCA
Schibsted A	Norway	Schibsted
SEB A	Sweden	SEB
Securitas B	Sweden	Securitas
SimCorp	Denmark	SimCorp
Skanska B	Sweden	Skanska
SKF B	Sweden	SKF
SSAB	Sweden	SSAB
Stora Enso Oyj R	Finland	Stora Enso
Storebrand	Norway	Subsea 7
Subsea 7	Norway	Subsea 7
Svenska Handelsbanken	Sweden	Svenska Handelsbanken
SWECO B	Sweden	SWECO
Swedbank A	Sweden	Swedbank
Swedish Match	Sweden	Swedish Match
Swedish Orphan Biovitrum AB	Sweden	Swedish Orphan Biovitrum
Tele2	Sweden	Tele2
Telenor	Norway	Telenor
Telia Company	Sweden	Telia Comany
TGS-NOPEC Geoph. Company	Norway	TGS-NOPEC
Thule Group	Sweden	Thule Group
Tomra Systems	Norway	Tomra Systems
Topdanmark	Denmark	Topdanmark
Trelleborg B	Sweden	Trelleborg AB
Tryg	Denmark	Tryg
UPM-Kymmene	Finland	UPM-Kymmene
Valmet	Finland	Valmet
Vestas Wind Systems	Denmark	Vestas Wind Systems
Volvo B	Sweden	Volvo
Wartsila	Finland	Wartsila
Yara International	Norway	Yara International

Appendix B

(1) Welch-Satterthwaite Equation:

$$df = \frac{(\frac{s_L^2}{n_L} + \frac{s_S^2}{n_S})^2}{\frac{(\frac{s_L^2}{n_L})^2}{n_L - 1} + \frac{(\frac{s_S^2}{n_S})^2}{n_S - 1}} \tag{15}$$

where df denotes degrees of freedom, s_L^2 and s_S^2 the sample variances, and n_L and n_S the sample sizes of the Large Δ portfolio and the Small Δ portfolio, respectively.

(2) Variance Inflation Factor:

$$VIF_j = \frac{1}{(1 - R_j^2)} \tag{16}$$

where VIF_j denotes the variance inflation factor for slope coefficient j and R_j^2 the R-squared from regressing slope coefficient j on all other independent variables (and including an intercept).

(3) VIF Test Results:

Coefficient	MKT	SMB	HML	WML
Test statistic	1.1496	1.0358	1.0347	1.1507

Appendix C

Table C1: Single-sorted portfolios: Next month abnormal trading activity

Variable	Δ Search Volume Small Δ	Medium Δ	Large Δ	Difference Large-Small	95% CI Lower	Upper
Panel A: Local Google search volume						
AVO_{t+1}	−0.38	0.59	0.58	0.96	−0.33	2.24
$\$AVO_{t+1}$	−0.38	0.52	0.89	1.27*	−0.05	2.60
ATO_{t+1}	−0.65	0.75	0.49	1.14	−0.26	2.54
$AILLIQ_{t+1}$	0.49	0.11	−1.05	−1.54**	−3.03	−0.06
Panel B: Global Google search volume						
AVO_{t+1}	−0.42	0.17	0.86	1.28*	0.00	2.56
$\$AVO_{t+1}$	−0.40	0.13	1.08	1.48**	0.16	2.80
ATO_{t+1}	−0.42	0.03	0.85	1.27*	−0.11	2.65
$AILLIQ_{t+1}$	0.02	0.33	−0.36	−0.38	−1.86	1.11

This table depicts average next month abnormal trading activity of monthly portfolios, which consist of stocks sorted according to their signed changes in Google search volume. AVO_{t+1} is the next month abnormal share volume, $\$AVO_{t+1}$ the next month abnormal dollar volume, ATO_{t+1} the next month abnormal turnover rate, and $AILLIQ_t$ the next month abnormal illiquidity ratio in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C2: Double-sorted portfolios: Abnormal share volume

Tercile	Δ Search Volume Small Δ	Medium Δ	Large Δ	Difference Large-Small	95% CI Lower	Upper
Panel A: Local Google search volume						
By Size						
1	0.39	0.15	3.63	3.24**	0.04	6.46
2	−1.37	0.29	3.40	4.77***	2.30	7.23
3	−0.64	0.41	0.18	0.82	−0.81	2.45
By Book-to-Market						
1	−1.62	−0.97	2.96	4.58***	2.19	6.98
2	−0.07	0.13	2.26	2.33*	−0.12	4.78
3	0.00	0.76	3.11	3.11**	0.34	5.87
By Current Month Return						
1	−0.14	0.78	2.66	2.80**	0.66	4.94
2	−5.06	−4.40	−3.35	1.71	−0.43	3.84
3	3.48	2.61	6.14	2.66**	0.16	5.17
By Amihud's (2002) Illiquidity Ratio						
1	0.96	1.66	2.05	1.09	−0.50	2.69
2	−0.20	1.33	5.28	5.48***	2.83	8.14
3	−2.03	−3.70	0.85	2.88*	−0.22	5.99
Panel B: Global Google search volume						
By Size						
1	−0.34	−0.43	5.96	6.30***	2.60	10.00
2	0.13	0.20	2.09	1.96*	−0.29	4.22
3	−1.03	0.04	0.84	1.87**	0.22	3.51
By Book-to-Market						
1	−1.28	−0.79	2.39	3.67***	1.43	5.91
2	0.46	−0.85	3.49	3.03**	0.31	5.73
3	0.17	0.27	3.69	3.52**	0.38	6.66
By Current Month Return						
1	−0.54	−0.23	3.16	3.70***	1.63	5.78
2	−4.46	−4.20	−4.16	0.30	−1.64	2.25
3	3.93	2.74	5.81	1.88	−0.59	4.35
By Amihud's (2002) Illiquidity Ratio						
1	0.88	1.11	2.31	1.43*	−0.17	3.03
2	0.98	1.22	5.59	4.61***	1.97	7.25
3	−2.11	−5.13	2.47	4.58**	1.01	8.15

This table depicts the average contemporaneous abnormal share volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Abnormal share volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C3: Double-sorted portfolios: Abnormal turnover rate

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−0.09	0.14	4.12	4.21**	0.79	7.62
2	−1.85	0.42	3.13	4.98***	2.40	7.57
3	−0.87	0.22	0.33	1.20	−0.67	3.06
By Book-to-Market						
1	−2.24	−0.37	2.88	5.12***	2.49	7.73
2	−0.41	0.11	2.41	2.82**	0.25	5.38
3	−0.76	0.91	3.14	3.90***	0.97	6.83
By Current Month Return						
1	−0.84	0.67	2.57	3.41***	1.13	5.69
2	−5.57	−4.01	−3.37	2.20*	−0.15	4.56
3	3.32	2.95	6.04	2.72**	0.07	5.38
By Amihud's (2002) Illiquidity Ratio						
1	0.63	1.64	2.09	1.46	−0.33	3.26
2	−0.52	1.52	5.06	5.58***	2.83	8.32
3	−2.67	−3.64	1.20	3.87**	0.51	7.23
Panel B: Global Google search volume						
By Size						
1	−0.61	−0.32	6.51	7.12***	3.27	10.98
2	0.30	−0.20	1.87	1.57	−0.80	3.94
3	−1.62	0.23	0.70	2.32**	0.52	4.12
By Book-to-Market						
1	−1.58	−1.08	2.81	4.39***	1.95	6.83
2	0.00	−0.53	3.48	3.48**	0.67	6.27
3	0.01	0.36	3.51	3.50**	0.25	6.74
By Current Month Return						
1	−0.85	−0.56	2.89	3.74***	1.53	5.93
2	−4.75	−4.16	−4.20	0.55	−1.50	2.61
3	4.01	2.87	6.09	2.08	−0.54	4.71
By Amihud's (2002) Illiquidity Ratio						
1	0.51	1.15	2.28	1.77*	−0.01	3.55
2	1.03	1.25	5.27	4.24***	1.54	6.93
3	−2.58	−5.26	3.08	5.66***	1.90	9.42

This table depicts the average contemporaneous abnormal turnover rate of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. The abnormal turnover rate is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table C4: Double-sorted portfolios: Abnormal illiquidity ratio

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	0.61	0.55	1.37	0.76	−2.53	4.06
2	0.13	−0.46	−1.59	−1.72	−3.99	0.55
3	−0.70	−0.44	−1.36	−0.66	−2.80	1.49
By Book-to-Market						
1	−0.69	−2.22	−0.82	−0.13	−2.68	2.41
2	−0.24	1.12	−1.12	−0.88	−3.47	1.71
3	0.74	0.80	0.66	−0.08	−2.85	2.70
By Current Month Return						
1	0.19	0.12	−0.09	−0.28	−2.85	2.29
2	1.80	0.65	0.74	−1.06	−3.72	1.59
3	−1.54	−1.37	−2.21	−0.67	−3.38	2.03
Panel B: Global Google search volume						
By Size						
1	1.51	1.24	0.85	−0.66	−3.92	2.60
2	−0.54	−0.15	−1.75	−1.21	−3.44	1.01
3	−1.21	−0.56	−0.28	0.93	−1.12	2.98
By Book-to-Market						
1	−1.61	−1.20	−0.46	1.15	−1.32	3.63
2	−0.21	0.45	−1.06	−0.85	−3.38	1.68
3	1.05	1.71	0.55	−0.50	−3.23	2.21
By Current Month Return						
1	0.43	−0.20	0.44	0.01	−2.59	2.62
2	−0.21	1.56	1.53	1.74	−0.72	4.19
3	1.55	−0.73	−1.63	−0.08	−2.78	2.62

This table depicts the average contemporaneous abnormal illiquidity ratio of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. The abnormal illiquidity ratio is based on Amihud's (2002) illiquidity ratio and given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix D

Table D1: Single-sorted portfolios: Stock characteristics

Variable	Δ Search Volume: Small Δ	Medium Δ	Large Δ	Difference: Large-Small	95% CI: Lower	Upper
			Panel A: Local Google search volume			
AVO	−1.40	0.44	3.33	4.73***	3.30	6.15
$AVO	−1.22	0.29	3.58	4.80***	3.34	6.25
ATO	−1.69	0.29	3.46	5.14***	3.62	6.67
AILLIQ	0.61	0.19	−1.43	−2.05***	−3.55	−0.54
RET	1.51	1.51	1.30	−0.21	−0.56	0.14
MV	8.93	10.04	9.09	0.15	−0.31	0.62
BTMV	0.54	0.57	0.54	0.00	−0.01	0.02
			Panel B: Global Google search volume			
AVO	−1.57	0.56	3.67	5.24***	3.80	6.68
$AVO	−1.56	0.73	3.62	5.18***	3.72	6.64
ATO	−1.79	0.39	3.87	5.66***	4.14	7.17
AILLIQ	0.37	−0.03	−0.82	−1.19	−2.66	0.28
RET	1.40	1.48	1.58	0.18	−0.17	0.52
MV	9.03	10.46	8.89	−0.14	−0.58	0.31
BTMV	0.55	0.55	0.56	0.01	−0.01	0.02

This table depicts average stock characteristics of monthly portfolios, which consist of stocks sorted according to their abnormal Google search volume. For each portfolio, equally weighted averages of contemporaneous monthly abnormal trading activity, monthly stock characteristics, and next month returns are computed. *AVO* is the abnormal share volume, *$AVO* the abnormal dollar volume, *ATO* the abnormal turnover rate, and *AILLIQ* the abnormal illiquidity ratio in %. *RET* gives the one-month return in %. *MV* is the market capitalization in billion USD and *BTMV* the book-to-market value. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D2: Single-sorted portfolios: Risk factor exposures

Coefficient	Small Δ	Medium Δ	Large Δ
	Panel A: Local Google search volume		
CAPM			
$MKT-RF$	0.9944***	1.0521***	0.9820***
FF-Three-Factor			
$MKT-RF$	0.9919***	1.0515***	0.9860***
SMB	0.0507	0.0067	0.1162*
HML	0.1355**	0.0264	0.0424
C-Four-Factor			
$MKT-RF$	0.9702***	1.0306***	0.9773***
SMB	0.0293	−0.0138	0.1076*
HML	0.1089*	0.0009	0.0317
WML	−0.1311***	−0.1260***	−0.0530
	Panel B: Global Google search volume		
CAPM			
$MKT-RF$	0.9970***	0.9798***	1.0534***
FF-Three-Factor			
$MKT-RF$	0.9998***	0.9789***	1.0543***
SMB	0.0872	0.0807	0.0746
HML	0.0388	0.1299**	0.0732
C-Four-Factor			
$MKT-RF$	0.9874***	0.9577***	1.0408***
SMB	0.0750	0.0599	0.0614
HML	0.0236	0.1040*	0.0567
WML	−0.0750*	−0.1277	−0.0813**

This table depicts the coefficients from regressions of portfolio excess returns in the month following formation (i.e., next month portfolio return minus one-month U.S. T-Bill rate) on recognized risk factors for the Nordic market. The portfolios consist of stocks, which are sorted according to abnormal Google search volume. Three different factor models are presented. $MKT-RF$ denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D3: Double-sorted portfolios: Abnormal share volume

Tercile	Δ Search Volume			Difference	95% CI	
	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−0.92	−0.29	5.88	6.80***	3.55	10.05
2	−1.87	1.60	2.80	4.67***	2.51	6.82
3	−1.69	0.50	1.41	3.10***	1.46	4.75
By Book-to-Market						
1	−2.30	−0.44	3.49	5.79***	3.36	8.23
2	−1.68	0.01	3.82	5.50***	2.77	8.23
3	0.15	1.41	3.02	2.88**	0.38	5.38
By Current Month Return						
1	−0.72	0.64	3.73	4.45***	2.29	6.60
2	−5.66	−3.76	−3.08	2.58***	0.63	4.52
2	2.04	3.85	6.66	4.61***	2.23	7.00
By Amihud's (2002) Illiquidity Ratio						
1	0.00	2.25	2.59	2.59***	0.99	4.19
2	−1.87	2.64	5.83	7.70***	5.15	10.25
3	−2.08	−3.34	1.28	3.36**	0.25	6.47
Panel B: Global Google search volume						
By Size						
1	−1.51	1.09	6.23	7.74***	4.40	11.08
2	−0.83	−0.49	3.81	4.64***	2.27	7.00
3	−1.33	0.03	1.20	2.53***	0.94	4.12
By Book-to-Market						
1	−2.12	−1.01	3.82	5.94***	3.56	8.31
2	−1.30	0.70	4.05	5.35***	2.86	7.84
3	−0.02	1.29	2.85	2.87**	0.16	5.58
By Current Month Return						
1	−0.35	−0.99	4.30	4.65***	2.45	6.85
2	−5.91	−3.83	−2.96	2.95***	0.89	5.01
3	2.10	3.87	6.70	4.61***	2.26	6.96
By Amihud's (2002) Illiquidity Ratio						
1	0.52	1.05	2.84	2.32***	0.76	3.88
2	−0.27	0.88	7.50	7.78***	5.00	10.55
3	−3.51	−2.88	2.06	5.57***	2.24	8.90

This table depicts the average contemporaneous abnormal share volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their abnormal Google search volume. Abnormal share volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D4: Double-sorted portfolios: Abnormal dollar volume

Tercile	Δ Search Volume			Difference	95% CI	
	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−1.70	−1.60	5.17	6.87***	3.53	10.21
2	−0.99	1.48	3.66	4.64***	2.42	6.87
3	−0.92	1.00	2.21	3.13***	1.51	4.76
By Book-to-Market						
1	−0.74	0.27	5.45	6.19***	3.69	8.69
2	−1.54	0.09	3.60	5.14***	2.39	7.89
3	−1.14	0.43	1.81	2.95**	0.42	5.49
By Current Month Return						
1	−0.94	−0.53	3.12	4.06***	1.87	6.24
2	−5.32	−3.50	−3.08	2.25**	0.25	4.24
3	2.60	4.31	8.06	5.46***	2.94	7.99
By Amihud's (2002) Illiquidity Ratio						
1	0.69	2.71	3.35	2.67***	1.07	4.26
2	−1.57	2.17	6.35	7.91***	5.33	10.50
3	−2.61	−4.01	1.05	3.65**	0.46	6.85
Panel B: Global Google search volume						
By Size						
1	−2.72	0.11	5.24	7.95***	4.53	11.37
2	−0.43	−0.25	4.63	5.06***	2.65	7.47
3	−0.56	0.88	1.78	2.34***	0.77	3.91
By Book-to-Market						
1	−0.72	0.38	5.36	6.08***	3.65	8.51
2	−1.59	0.93	3.88	5.47***	2.97	7.98
3	−1.11	−0.02	1.47	2.58*	−0.18	5.34
By Current Month Return						
1	−1.09	−1.46	3.33	4.41***	2.24	6.59
2	−5.70	−3.83	−2.51	3.19***	1.10	5.28
3	2.81	4.42	7.54	4.73***	2.25	7.21
By Amihud's (2002) Illiquidity Ratio						
1	1.05	1.81	3.47	2.42***	0.88	3.97
2	−0.39	0.97	7.71	8.10***	5.32	10.87
3	−4.09	−3.51	1.55	5.64***	2.22	9.06

This table depicts the average contemporaneous abnormal dollar volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their abnormal Google search volume. Abnormal dollar volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D5: Double-sorted portfolios: Abnormal turnover rate

Tercile	Δ Search Volume Small Δ	Medium Δ	Large Δ	Difference Large-Small	95% CI Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−1.02	−0.15	5.94	6.95***	3.54	10.36
2	−2.12	0.99	2.94	5.06***	2.75	7.37
3	−1.97	0.42	1.49	3.46***	1.61	5.31
By Book-to-Market						
1	−2.22	−0.50	3.33	5.56***	2.89	8.23
2	−1.83	−0.14	3.89	5.72***	2.90	8.54
3	−0.46	1.29	3.21	3.67***	0.96	6.38
By Current Month Return						
1	−1.02	0.25	3.47	4.49***	2.19	6.79
2	−6.08	−3.48	−3.24	2.83***	0.75	4.92
3	2.01	3.70	7.11	5.10***	2.54	7.65
By Amihud's (2002) Illiquidity Ratio						
1	−0.36	2.26	2.62	2.99***	1.21	4.77
2	−1.69	2.23	5.67	7.36***	4.69	10.03
3	−2.40	−3.51	1.59	3.99**	0.61	7.36
Panel B: Global Google search volume						
By Size						
1	−1.22	1.14	6.35	7.57***	4.08	11.05
2	−1.25	−0.57	3.80	5.05***	2.56	7.54
3	−1.83	−0.17	1.42	3.25***	1.48	5.03
By Book-to-Market						
1	−2.56	−1.08	4.14	6.70***	4.13	9.27
2	−1.06	0.65	3.78	4.83***	2.26	7.41
3	−0.63	1.37	3.12	3.75***	0.91	6.60
By Current Month Return						
1	−0.72	−1.57	4.32	5.04***	2.70	7.38
2	−6.11	−3.98	−2.92	3.19***	0.98	5.40
3	2.02	4.64	6.59	4.57***	2.11	7.03
By Amihud's (2002) Illiquidity Ratio						
1	−0.16	0.95	3.33	3.49***	1.75	5.22
2	−0.44	0.91	7.35	7.79***	4.95	10.63
3	−3.46	−2.88	2.07	5.52***	2.01	9.04

This table depicts the average contemporaneous abnormal turnover rate of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their abnormal Google search volume. The abnormal turnover rate is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D6: Double-sorted portfolios: Next month returns

Tercile	Δ Search Volume Small Δ	Medium Δ	Large Δ	Difference Large-Small	95% CI Lower	Upper
Panel A: Local Google search volume						
By Size						
1	2.07	2.23	1.89	−0.18	−0.84	0.48
2	1.22	1.51	1.28	0.07	−0.54	0.67
3	1.09	0.94	0.66	−0.43	−0.98	0.12
By Book-to-Market						
1	1.25	1.46	1.24	−0.01	−0.58	0.56
2	1.70	1.70	1.13	−0.57*	−1.18	0.03
3	1.54	1.38	1.53	−0.01	−0.67	0.65
By Current Month Return						
1	1.64	1.55	1.44	−0.20	−0.84	0.45
2	1.53	1.49	1.42	−0.11	−0.70	0.47
3	1.30	1.44	1.08	−0.22	−0.82	0.37
By Amihud's (2002) Illiquidity Ratio						
1	1.19	1.06	0.82	−0.37	−0.93	0.20
2	1.14	1.55	1.12	−0.02	−0.63	0.60
3	2.10	2.21	1.77	−0.33	−0.98	0.32
Panel B: Global Google search volume						
By Size						
1	1.96	2.35	2.18	0.23	−0.43	0.88
2	1.26	1.54	1.29	0.03	−0.56	0.61
3	0.87	0.93	0.98	0.10	−0.43	0.63
By Book-to-Market						
1	1.18	1.24	1.45	0.27	−0.29	0.83
2	1.53	1.72	1.61	0.08	−0.52	0.68
3	1.50	1.48	1.68	0.18	−0.46	0.82
By Current Month Return						
1	1.42	1.79	1.66	0.23	−0.39	0.85
2	1.43	1.53	1.57	0.15	−0.42	0.72
3	1.24	1.37	1.31	0.07	−0.52	0.65
By Amihud's (2002) Illiquidity Ratio						
1	1.03	1.11	0.93	−0.10	−0.65	0.44
2	1.24	1.55	1.26	0.02	−0.58	0.61
3	1.89	2.13	2.26	0.37	−0.27	1.01

This table depicts the average next month returns of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their abnormal Google search volume. The next month return is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D7: Factor models: Local Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
Panel A: Coefficients for long-short strategy				
MKT − RF	-	0.0125	0.0059	−0.0070
		(0.0256)	(0.0260)	(0.0274)
SMB	-	-	−0.0655	−0.0782
			(0.0742)	(0.0745)
HML	-	-	0.0930	0.0772
			(0.0761)	(0.0767)
WML	-	-	-	−0.0781
				(0.0526)
Intercept	0.2049	0.1947	0.1825	0.2799*
	(0.1536)	(0.1553)	(0.1556)	(0.1684)
Observations	190	190	190	190
R^2		0.0013	0.0128	0.0244
Panel B: Alphas for low AGSV stocks (Long)				
Intercept	1.4454***	0.6327***	0.6360***	0.7994***
	(0.4500)	(0.1175)	(0.1164)	(0.1228)
Panel C: Alphas for high AGSV stocks (Short)				
Intercept	1.2405***	0.4380***	0.4535***	0.5196***
	(0.4499)	(0.1360)	(0.1357)	(0.1471)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with low abnormal local Google search volume and short in a portfolio of stocks with high abnormal local Google search volume. The portfolios are formed each month by sorting stocks into three quantiles of equal size according to their abnormal local Google search volume. The equal-weighted average returns of this strategy in the month following portfolio formation are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. *MKT − RF* denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. Panel B and C show intercepts from the regressions of excess returns (i.e., portfolio return minus one-month U.S. T-Bill rate) on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table D8: Factor models: Global Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
Panel A: Coefficients for long-short strategy				
MKT − RF	-	0.0564**	0.0545**	0.0535*
		(0.0252)	(0.0257)	(0.0272)
SMB	-	-	−0.0126	−0.0136
			(0.0734)	(0.0741)
HML	-	-	0.0345	0.0332
			(0.0754)	(0.0763)
WML	-	-	-	−0.0063
				(0.0523)
Intercept	0.1811	0.1350	0.1322	0.1400
	(0.1531)	(0.1529)	(0.1540)	(0.1676)
Observations	190	190	190	190
R^2		0.0260	0.0271	0.0272
Panel B: Alphas for high AGSV stocks (Long)				
Intercept	1.5246***	0.6637***	0.6723***	0.7736***
	(0.4742)	(0.1143)	(0.1140)	(0.1226)
Panel C: Alphas for low AGSV stocks (Short)				
Intercept	1.3435***	0.5287***	0.5401***	0.6336***
	(0.4545)	(0.1302)	(0.1304)	(0.1408)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with high abnormal local Google search volume and short in a portfolio of stocks with low abnormal local Google search volume. The portfolios are formed each month by sorting stocks into three quantiles of equal size according to their abnormal local Google search volume. The equal-weighted average returns of this strategy in the month following portfolio formation are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. *MKT − RF* denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. Panel B and C show intercepts from the regressions of monthly excess returns (i.e., portfolio return minus one-month U.S. T-Bill rate) on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix E

Table E1: Single-sorted portfolios: Stock characteristics

	Δ Search Volume			Difference	95% CI	
Variable	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
AVO	−0.94	0.20	2.80	3.74***	2.29	5.19
$*AVO*	−0.75	0.24	2.87	3.63***	2.15	5.10
ATO	−1.22	0.10	2.90	4.13***	2.58	5.67
AILLIQ	−0.33	0.38	−0.67	−0.35	−1.81	1.14
RET	1.42	1.34	1.52	0.11	−0.25	0.46
MV	10.07	9.40	8.84	−1.23***	−1.72	−0.75
BTMV	0.54	0.55	0.54	0.00	−0.01	0.02

This table depicts average stock characteristics of monthly portfolios, which consist of stocks sorted according to their combined score for local and global Google search volume. For each portfolio, equally weighted averages of contemporaneous monthly abnormal trading activity, monthly stock characteristics, and next month returns are computed. *AVO* is the abnormal share volume, $*AVO* the abnormal dollar volume, *ATO* the abnormal turnover rate, and *AILLIQ* the abnormal illiquidity ratio in %. *RET* gives the one-month return in %. *MV* is the market capitalization in billion USD and *BTMV* the book-to-market value. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table E2: Single-sorted portfolios: Risk factor exposures

Coefficient	Small Δ	Medium Δ	Large Δ
CAPM			
$MKT-RF$	1.0114***	1.0334***	0.9908***
FF-Three-Factor			
$MKT-RF$	1.0097***	1.0336***	0.9934***
SMB	0.0529	0.0348	0.0813
HML	0.1158***	0.0422	0.0360
C-Four-Factor			
$MKT-RF$	0.9793***	1.0132***	0.9905***
SMB	0.0229	0.0147	0.0784
HML	0.0785	0.0172	0.0325
WML	−0.1837***	−0.1233***	−0.0175

This table depicts the coefficients from regressions of portfolio excess returns in the month following formation (i.e., next month portfolio return minus one-month U.S. T-Bill rate) on recognized risk factors for the Nordic market. The portfolios consist of stocks, which are sorted according to their combined score for local and global Google search volume. Three different factor models are presented. $MKT-RF$ denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table E3: Double-sorted portfolios: Abnormal share volume

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
By Size						
1	−0.45	−0.11	4.70	5.15***	1.81	8.49
2	−0.91	0.22	3.28	4.19***	1.90	6.48
3	−1.31	0.25	0.66	1.97**	0.33	3.61
By Book-to-Market						
1	−1.72	−1.21	3.31	5.03***	2.54	7.53
2	0.20	−0.72	2.78	2.58*	−0.11	5.27
3	−0.86	2.42	2.22	3.09**	0.68	5.50
By Current Month Return						
1	−0.98	0.88	3.52	4.50***	2.37	6.63
2	−4.92	−4.87	−3.17	1.75*	−0.32	3.82
3	3.87	2.06	6.25	2.38*	−0.15	4.91
By Amihud's (2002) Illiquidity Ratio						
1	0.19	1.83	2.64	2.45***	0.86	4.04
2	0.09	0.75	5.77	5.68***	2.95	8.41
3	−3.15	−2.60	0.79	3.94**	0.88	7.00

This table depicts the average contemporaneous abnormal share volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their combined score for local and global Google search volume. Abnormal share volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table E4: Double-sorted portfolios: Abnormal dollar volume

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
By Size						
1	−1.39	−0.99	3.85	5.24***	1.82	8.66
2	−0.50	0.51	4.05	4.55***	2.22	6.88
3	−0.35	0.76	1.39	1.73**	0.09	3.38
By Book-to-Market						
1	−0.23	−0.13	4.94	5.17***	2.61	7.74
2	0.30	−0.79	2.86	2.56*	−0.15	5.28
3	−2.02	1.26	1.07	3.09**	0.66	5.52
By Current Month Return						
1	−1.51	0.21	2.69	4.21***	2.06	6.35
2	−4.66	−5.02	−2.68	1.98*	−0.10	4.05
3	4.84	2.67	7.23	2.40*	−0.28	5.07
By Amihud's (2002) Illiquidity Ratio						
1	0.99	2.32	3.38	2.39***	0.80	3.98
2	0.13	0.76	5.95	5.81***	3.08	8.55
3	−3.66	−3.05	0.37	4.03**	0.88	7.17

This table depicts the average contemporaneous abnormal dollar volume of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their combined score for local and global Google search volume. Abnormal dollar volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table E5: Double-sorted portfolios: Abnormal turnover rate

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
By Size						
1	−1.03	−0.13	5.41	6.45***	2.91	9.99
2	−0.95	−0.03	2.97	3.92***	1.54	6.30
3	−1.70	0.39	0.63	2.33**	0.47	4.19
By Book-to-Market						
1	−2.19	−1.02	3.47	5.66***	2.95	8.37
2	−0.06	−0.76	3.01	3.07**	0.27	5.86
3	−1.02	2.03	2.18	3.20**	0.56	5.83
By Current Month Return						
1	−1.26	0.01	3.78	5.04***	2.76	7.33
2	−5.46	−4.53	−3.17	2.29**	0.01	4.58
3	3.67	2.38	6.39	2.73**	0.05	5.41
By Amihud's (2002) Illiquidity Ratio						
1	0.00	1.75	2.61	2.60***	0.81	4.40
2	−0.09	0.79	5.50	5.59***	2.77	8.41
3	−3.58	−3.23	1.79	5.37***	2.04	8.69

This table depicts the average contemporaneous abnormal turnover rate of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their combined score for local and global Google search volume. The abnormal turnover rate is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table E6: Double-sorted portfolios: Next month returns

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
By Size						
1	2.14	1.88	2.21	0.08	−0.61	0.76
2	1.28	1.38	1.14	−0.14	−0.74	0.46
3	0.89	0.91	0.95	0.05	−0.51	0.61
By Book-to-Market						
1	1.17	1.17	1.53	0.36	−0.22	0.95
2	1.48	1.63	1.36	−0.12	−0.73	0.48
3	1.51	1.51	1.48	−0.03	−0.70	0.64
By Current Month Return						
1	1.42	1.49	1.73	0.31	−0.34	0.96
2	1.55	1.52	1.24	−0.31	−0.90	0.28
3	1.25	1.30	1.28	0.02	−0.60	0.64
By Amihud's (2002) Illiquidity Ratio						
1	1.06	1.05	0.97	−0.09	−0.66	0.47
2	1.33	1.00	1.32	−0.02	−0.65	0.62
3	1.99	2.04	2.12	0.13	−0.53	0.79

This table depicts the average next month returns of monthly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their combined score for local and global Google search volume. Next month returns are given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix F

Table F1: Single-sorted portfolios: Stock characteristics

	Δ Search Volume			Difference	95% CI	
Variable	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
			Panel A: Local Google search volume			
AVO	3.42	0.11	2.50	−0.92	−2.67	0.83
$AVO	3.40	0.31	2.68	−0.73	−2.48	1.03
ATO	2.79	−0.22	1.92	−0.86	−2.65	0.93
AILLIQ	−1.89	0.12	−0.45	1.44*	−0.01	2.89
RET	0.28	0.22	0.30	0.03	−0.10	0.16
MV	11.05	12.33	10.39	−0.66***	−1.10	−0.23
BTMV	0.48	0.49	0.48	0.01	−0.01	0.02
			Panel B: Global Google search volume			
AVO	2.97	0.99	1.61	−1.37	−3.11	0.38
$AVO	3.14	0.85	1.86	−1.28	−3.02	0.47
ATO	2.39	0.67	1.07	−1.31	−3.09	0.47
AILLIQ	−0.93	−0.51	−0.37	0.55	−0.79	1.90
RET	0.26	0.28	0.27	0.01	−0.11	0.13
MV	10.82	12.21	10.16	−0.66***	−1.06	−0.27
BTMV	0.49	0.47	0.49	0.00	−0.01	0.02

This table depicts average stock characteristics of weekly portfolios, which consist of stocks sorted according their signed changes in Google search volume. For each portfolio, equally weighted averages of contemporaneous weekly abnormal trading activity, weekly stock characteristics, and next week returns are computed. *AVO* is the abnormal share volume, *$AVO* the abnormal dollar volume, *ATO* the abnormal turnover rate, and *AILLIQ* the abnormal illiquidity ratio in %. *RET* gives the one-week return in %. *MV* is the market capitalization in billion USD and *BTMV* the book-to-market value. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F2: Double-sorted portfolios: Abnormal share volume

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
			Panel A: Local Google search volume			
By Size						
1	−1.16	−0.60	3.92	5.09***	2.03	8.14
2	−1.05	−0.86	2.23	3.27**	0.53	6.01
3	−0.71	−1.50	2.84	3.54***	1.00	6.08
By Book-to-Market						
1	−1.26	−2.77	4.89	6.16***	3.28	9.03
2	−0.82	−0.33	1.38	2.20	−0.54	4.93
3	−0.42	−0.62	3.08	3.50**	0.69	6.31
By Current Month Return						
1	2.44	0.09	4.06	1.63	−1.32	4.57
2	−5.47	−4.58	−0.21	5.26***	2.72	7.80
3	0.40	0.67	5.13	4.73***	1.99	7.46
By Amihud's (2002) Illiquidity Ratio						
1	−0.04	−1.45	4.29	4.33	1.96	6.70
2	0.15	−0.07	4.22	4.07***	1.25	6.90
3	−2.78	−2.52	0.53	3.32**	0.31	6.33
			Panel B: Global Google search volume			
By Size						
1	−0.59	0.44	3.21	3.80**	0.58	7.02
2	−1.69	−1.95	1.74	3.43***	0.91	5.95
3	−1.78	−0.88	1.80	3.57***	1.22	5.93
By Book-to-Market						
1	−2.18	−1.49	2.42	4.59***	1.95	7.24
2	−1.49	−0.06	1.93	3.42**	0.24	6.59
3	−1.03	−1.00	3.28	4.31***	1.67	6.95
By Current Month Return						
1	0.16	1.84	4.84	4.68***	1.84	7.52
2	−5.11	−3.55	−2.38	2.73**	0.34	5.11
3	0.55	−0.81	4.17	3.62**	0.67	6.58
By Amihud's (2002) Illiquidity Ratio						
1	−1.13	−0.31	2.89	4.01***	1.86	6.16
2	0.07	0.72	2.82	2.75**	0.15	5.34
3	−2.90	−3.98	1.54	4.45**	0.89	8.00

This table depicts the average next week abnormal share volume of weekly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Abnormal share volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F3: Double-sorted portfolios: Abnormal dollar volume

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−1.98	−1.14	3.43	5.42***	2.41	8.42
2	−0.24	−0.23	3.05	3.29**	0.50	6.07
3	−0.38	−1.00	3.30	3.68***	1.20	6.16
By Book-to-Market						
1	0.37	−1.06	6.38	6.01***	3.13	8.90
2	−1.15	−0.04	1.05	2.20	−0.51	4.91
3	−1.51	−1.86	2.56	4.07***	1.32	6.82
By Current Month Return						
1	0.74	−1.40	2.36	1.61	−1.22	4.45
2	−5.05	−4.19	0.27	5.33***	2.77	7.88
3	2.00	2.63	7.01	5.00***	2.24	7.77
By Amihud's (2002) Illiquidity Ratio						
1	−0.04	−1.45	4.29	4.33***	1.96	6.70
2	0.15	−0.07	4.22	4.07***	1.25	6.90
3	−2.78	−2.52	0.53	3.32**	0.31	6.33
Panel B: Global Google search volume						
By Size						
1	−1.15	−0.43	2.73	3.88**	0.70	7.06
2	−0.94	−1.44	2.69	3.64***	1.09	6.18
3	−1.58	−0.45	2.42	4.00***	1.70	6.31
By Book-to-Market						
1	−0.34	−0.16	4.23	4.57***	1.88	7.25
2	−1.82	−0.00	1.85	3.67**	0.55	6.79
3	−2.01	−2.13	2.20	4.21***	1.63	6.79
By Current Month Return						
1	−1.37	−0.03	3.29	4.66***	1.89	7.43
2	−4.63	−3.18	−1.91	2.72**	0.32	5.12
3	2.42	0.69	6.06	3.64**	0.67	6.60
By Amihud's (2002) Illiquidity Ratio						
1	−1.13	−0.31	2.89	4.01***	1.86	6.16
2	0.07	0.72	2.82	2.75**	0.15	5.34
3	−2.90	−3.98	1.54	4.45**	0.89	8.00

This table depicts the average next week abnormal dollar volume of weekly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Abnormal dollar volume is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F4: Double-sorted portfolios: Abnormal turnover rate

	Δ Search Volume			Difference	95% CI	
Tercile	Small Δ	Medium Δ	Large Δ	Large-Small	Lower	Upper
Panel A: Local Google search volume						
By Size						
1	−2.03	−0.82	3.25	5.28***	2.13	8.44
2	−1.82	−1.43	1.47	3.30**	0.49	6.11
3	−1.21	−1.63	2.57	3.78***	1.19	6.37
By Book-to-Market						
1	−2.88	−3.52	3.35	6.23***	3.22	9.25
2	−1.12	−0.58	1.56	2.68*	−0.11	5.48
3	−0.81	−0.49	2.92	3.73**	0.88	6.57
By Current Month Return						
1	1.48	−0.32	3.45	1.97	−1.04	4.97
2	−6.19	−4.88	−0.69	5.51***	2.89	8.13
3	−0.14	0.77	4.30	4.45***	1.63	7.27
By Amihud's (2002) Illiquidity Ratio						
1	−0.04	−1.45	4.29	4.33***	1.96	6.70
2	0.15	−0.07	4.22	4.07***	1.25	6.90
3	−2.78	−2.52	0.53	3.32**	0.31	6.33
Panel B: Global Google search volume						
By Size						
1	−1.20	0.05	2.68	3.88**	0.53	7.22
2	−2.45	−2.34	0.86	3.31**	0.74	5.89
3	−2.27	−1.16	1.62	3.89***	1.48	6.29
By Book-to-Market						
1	−3.78	−2.62	1.24	5.02***	2.24	7.79
2	−1.35	−0.07	1.88	3.23*	−0.01	6.47
3	−1.40	−1.08	3.09	4.49***	1.83	7.16
By Current Month Return						
1	−0.62	1.27	4.30	4.92***	2.00	7.84
2	−5.57	−4.02	−2.96	2.61**	0.15	5.07
3	−0.12	−1.05	3.99	4.11***	1.07	7.16
By Amihud's (2002) Illiquidity Ratio						
1	−1.13	−0.31	2.89	4.01***	1.86	6.16
2	0.07	0.72	2.82	2.75**	0.15	5.34
3	−2.90	−3.98	1.54	4.45**	0.89	8.00

This table depicts the average next week turnover rate of weekly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. The abnormal turnover rate is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F5: Double-sorted portfolios: Next week returns

Tercile	Δ Search Volume: Small Δ	Medium Δ	Large Δ	Difference: Large-Small	95% CI: Lower	Upper
Panel A: Local Google search volume						
By Size						
1	0.32	0.40	0.49	0.17	−0.07	0.41
2	0.17	0.32	0.27	0.10	−0.12	0.33
3	0.25	0.09	0.09	−0.16	−0.37	0.06
By Book-to-Market						
1	0.30	0.14	0.26	−0.05	−0.28	0.19
2	0.18	0.33	0.46	0.28**	0.06	0.50
3	0.30	0.20	0.23	−0.07	−0.31	0.16
By Current Month Return						
1	0.33	0.33	0.31	−0.02	−0.25	0.21
2	0.32	0.18	0.35	0.03	−0.19	0.25
3	0.18	0.15	0.24	0.07	−0.17	0.30
By Amihud's (2002) Illiquidity Ratio						
1	0.30	0.11	0.13	−0.17	−0.39	0.04
2	0.18	0.17	0.24	0.06	−0.16	0.29
3	0.31	0.49	0.51	0.19	−0.05	0.43
Panel B: Global Google search volume						
By Size						
1	0.36	0.49	0.40	0.04	−0.18	0.26
2	0.20	0.28	0.22	0.02	−0.18	0.23
3	0.17	0.19	0.12	−0.05	−0.25	0.15
By Book-to-Market						
1	0.24	0.24	0.28	0.04	−0.18	0.25
2	0.29	0.31	0.35	0.05	−0.15	0.25
3	0.23	0.23	0.25	0.01	−0.20	0.23
By Current Month Return						
1	0.37	0.35	0.29	−0.08	−0.30	0.13
2	0.31	0.24	0.32	0.01	−0.19	0.21
3	0.10	0.25	0.20	0.10	−0.12	0.32
By Amihud's (2002) Illiquidity Ratio						
1	0.22	0.18	0.14	−0.09	−0.28	0.11
2	0.16	0.20	0.21	0.05	−0.16	0.26
3	0.38	0.46	0.48	0.10	−0.13	0.32

This table depicts the average next week return of weekly portfolios, which consist of stocks first sorted according to various firm characteristics and then on their signed changes in Google search volume. Next week return is given in %. CI denotes lower- and upper bound of 95% confidence intervals for two-sample, two-sided Welch t-tests on the difference in means between the Large Δ portfolio and the Small Δ portfolio. The null hypothesis is stated as: "The difference in means between the two portfolios is zero". *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F6: Factor models: Local Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
Panel A: Coefficients for long-short strategy				
MKT − RF	-	−0.0357***	−0.0242	−0.0305**
		(0.0127)	(0.0151)	(0.0154)
SMB	-	-	0.0553*	0.0534
			(0.0332)	(0.0332)
HML	-	-	0.0198	−0.0100
			(0.0280)	(0.0320)
WML	-	-	-	−0.0449*
				(0.0234)
Intercept	0.0072	0.0078	0.0076	0.0092
	(0.0112)	(0.0111)	(0.0111)	(0.0112)
Observations	1,190	1,190	1,190	1,190
R^2		0.0066	0.0093	0.0123
Panel B: Alphas for *Large* Δ stocks (Long)				
Intercept	0.0458	0.0270**	0.0216*	0.0202*
	(0.0282)	(0.0127)	(0.0120)	(0.0120)
Panel C: Alphas for *Small* Δ stocks (Short)				
Intercept	0.0387	0.0192	0.0140	0.0111
	(0.0291)	(0.0128)	(0.0122)	(0.0122)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with large signed changes in local Google search volume and short in a portfolio of stocks with small signed changes in local Google search volume. The portfolios are formed each week by sorting stocks into three quantiles of equal size according to their signed changes in local Google search volume. The equal-weighted average daily returns of this strategy are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. *MKT − RF* denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. Panel B and C show intercepts from the regressions of daily excess returns on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table F7: Factor models: Global Google search volume

	Mean	CAPM	FF-Three-Factor	C-Four-Factor
		Panel A: Coefficients for long-short strategy		
MKT − RF	-	0.0138	0.0082	0.0118
		(0.0120)	(0.0144)	(0.0147)
SMB	-	-	−0.0283	−0.0272
			(0.0315)	(0.0315)
HML	-	-	−0.0137	0.0029
			(0.0266)	(0.0304)
WML	-	-	-	0.0251
				(0.0222)
Intercept	0.0077	0.0074	0.0075	0.0066
	(0.0106)	(0.0106)	(0.0106)	(0.0106)
Observations	1,190	1,190	1,190	1,190
R^2		0.0011	0.0020	0.0030
		Panel B: Alphas for *Large* Δ stocks (Long)		
Intercept	0.0550*	0.0357***	0.0304**	0.0281**
	(0.0289)	(0.0129)	(0.0122)	(0.0122)
		Panel C: Alphas for *Small* Δ stocks (Short)		
Intercept	0.0474*	0.0283**	0.0230**	0.0215*
	(0.0285)	(0.0127)	(0.0120)	(0.0120)

This table depicts the profitability of a trading strategy which goes long in a portfolio of stocks with large signed changes in global Google search volume and short in a portfolio of stocks with small changes in global Google search volume. The portfolios are formed each week by sorting stocks into three quantiles of equal size according to their signed changes in global Google search volume. The equal-weighted average daily returns of this strategy are then regressed on the intercept alone, as well as on the CAPM, the Fama-French (1993) three-factor model and the Carhart (1997) four-factor model. *MKT − RF* denotes a portfolio's exposure to the market factor, *SMB* its exposure to the size factor, *HML* its exposure to the value factor, and *WML* its exposure to the momentum factor. Panel B and C show intercepts from the regressions of daily excess returns on risk factors for the long- and short position of the zero-investment strategy separately. Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.