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Highlights

- We study whether Google searches predict stock market activity in Norway.
- Google searches neither correlate with nor predict future abnormal returns.
- Increased Google searches predict increased volatility and trading volume.
- Google searches are more related to future than current trading activity.

Google searches and stock market activity: evidence from Norway

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Abstract

We investigate whether Google searches can explain current and predict future abnormal returns, trading volume, and volatility of the largest companies listed on the Oslo Stock Exchange. Our results show that Google searches are neither correlated with contemporaneous nor able to predict future abnormal returns. However, increased Google searches predict increased volatility and trading volume. Altogether, Google searches are more related to future than current trading activity.

Keywords: Google searches, stock returns, volatility, trading volume

1. Introduction

Google's search engine is by far the most popular and highly utilized information gathering platform in the world. Close to 90% of internet searches are handled by this search giant worldwide and many businesses rely on being ranked highly in the platform's search results to attract attention from potential customers (Harford, 2017). Google also keeps track of statistics for various search queries made on their search engine and these are publicly available through their Google Trends (henceforth GT) webpage. Information offered by the platform has garnered attention from the research community and has been used to either identify trends or predict dynamics in various fields including influenza epidemics (Eysenbach, 2006; Polgreen et al., 2008; Ginsberg et al., 2009), automobile sales, unemployment claims, travel destination planning, consumer confidence (Choi and Varian, 2012), and gasoline prices (Molnár and Bašta, 2017).

The relation between Google searches and stock markets has recently also attracted a lot of attention. Google's search volume index (henceforth SVI) is now recognized to be a significant proxy for investor attention and investor sentiment (Da et al., 2011; Joseph et al., 2011). Da et al. (2011) find that an increase in SVI predicts higher stock prices in the following two weeks and a price reversal within the year. A similar result is found by Gwilym et al. (2016) for the Chinese stock market. Vozlyublennaia (2014) finds that attention does influence performance of indexes of stocks, bonds, and commodities.

Preis et al. (2013) find that Google searches can be utilized in profitable trading strategies. However, Challet and Ayed (2014) challenged their methodology and show that random finance-related keywords are not better indicators of exploitable predictive information compared to other random keywords. Bijl et al. (2016) find a trading strategy based on Google searches to be profitable before, but not after transaction costs.

Da et al. (2014) utilize internet search volume for queries related to household concerns to construct a Financial and Economic Attitudes Revealed by Search index as a new measure of investor sentiment and find that this index predicts not only short-term return reversals but also increases in volatility. Vlastakis and Markellos (2012) show that for the largest US companies, internet search volume is positively related to volatility and trading volume. The predictive power of Google searches on trading volume is also documented in Preis et al. (2010) and further evidence of the impact of Google searches on volatility is provided by Goddard et al. (2015). Dimpfl and Jank (2016) find that investor attention is not only correlated but also predicts the volatility of the US stock market.

Previous research on Google searches and stock markets has focused primarily on the US market, even though studies from other markets have also emerged. For the German stock market, both Bank et al. (2011) and Fink and Johann (2014) indicate that an increase in search queries is associated with a rise in trading activity. Aouadi et al.

(2013) find for the French stock market that investor attention is correlated to trading volume and determines stock market volatility. Takeda and Wakao (2014) document that in the Japanese stock market, online search activity is only weakly related to stock returns and is more strongly related to trading volume. Goddard et al. (2015) conclude that investor attention comoves with contemporaneous FX market volatility and predicts subsequent FX market volatility. On the other hand, Tantaopas et al. (2016) study the relationships between investor attention and return, volatility, and trading volume from selected Asia-Pacific equity markets and find causality mostly from market variables to attention. However, their analysis is conducted at index level, not at the level of individual companies.

We are interested in investigating a relatively smaller market to see whether earlier findings from the US and other relatively large markets also hold for this market. Da et al. (2011) suggest that SVI may actually be more pronounced for smaller companies. Therefore, it is of interest to study a smaller market, but a one with high internet penetration, high internet activity, and high utilization of Google's localized search engine. Norway meets these parameters, with the country's internet penetration rate reported at 96.8%,[1] daily internet access at 89%,[2] and Google's localized search engine ranked as the top site visited with users averaging 6:20 minutes daily with 7.47 daily unique page views.[3] Thus, our study focuses on the Norwegian stock market, the Oslo Stock Exchange (henceforth OSE).

We study the relation between SVI and returns, trading volume volatility of the largest companies traded on the OSE in two ways. First, we study the contemporary relationship between SVI and these three measures of market activity. Second, we investigate whether Google searches can even predict these variables. We find that even though Google searches do not predict or explain stock returns, the opposite is true for volatility and trading volume. Interestingly, Google trends have an even stronger relation to future trading volume and volatility than to current trading volume and volatility. Our conclusions are in line with the findings from other markets.

The rest of the paper is organized as follows. Section 2 presents the data used in the paper. The methodology is described in section 3. Section 4 presents our findings and a discussion of the results. In section 5 we check the robustness of our findings. Section 6 concludes.

2. Data

The data is obtained primarily from Yahoo! Finance, Google Trends, and Bernt Arne Ødegaard's online data library. The sample period is from January 2, 2012 to January 2, 2017. However, data from 2011 is also obtained and used because we standardize some of the variables with respect to their past values. Yahoo! Finance is used to collect daily open, close, high, low, adjusted close price, and the trading volume for the companies listed in the Oslo Børs Total Return Index (henceforth OBX). The Google Trends platform is used to obtain the SVI data. Pricing factors are obtained from the Bernt Arne Ødegaard's online data library.

All companies that were in the OBE index from 2012 to 2017 and have complete stock data have been included. We omit the companies with a low search volume on the search words for which Google does not provide any data at all. Our final sample consists of 28 companies.

2.1. Google Trends data

Google Trends is a real-time daily index of the volume of queries users enter into Google search engine. The platform also gives access to what it calls "non-real time data", which pertains to historical data from 2004 up to 36 hours prior to search activity. Non-real time data can be viewed and downloaded in different time ranges: past hour, past 4 hours, past day, past 7 days, past 30 days, past 90 days, past 12 months, past 5 years, 2004 to present, and custom time ranges. However, time frequency in the dataset varies according to the time range set by the user: for example, hourly data can be downloaded at most for one day only and daily data can be downloaded at once only for the time range up to 90 days. Google Trends uses a standardized scale of 0 to 100, where 100 represents the highest query volume during a considered time period and geographic region (Choi and Varian, 2012).

We conduct our analysis using weekly Google search data. Preis et al. (2010) show that there is a correlation between GT data for company names and the transaction volumes of the corresponding stocks on a weekly time scale.

[1] Data provided by World Bank, internet users as a percentage of the population, retrieved June 5, 2017.
[2] Data provided by Statistics Norway (SSB), retrieved June 5, 2017.
[3] Data provided by Alexa, retrieved June 5, 2017.

Bijl et al. (2016) find that a significant and negative relationship exists between weekly abnormal search volumes and subsequent stock returns.

To study the impact of Google SVI on the Norwegian stock market, the stock market data have to be matched with weekly Google SVI data. Google reports their trend data from Sunday to Sunday, while the Norwegian stock market reports data from Monday to Friday. To match the two datasets, we transform the daily stock market data into weekly observations, with a week defined from Monday to Monday. This procedure is described in more detail later in this section.

Bijl et al. (2016) conclude that company name searches have a stronger relationship to stock market returns than ticker searches. Based on this insight, we prioritized the use of words closest to the company's name and excluded words that are generally used in business names, such as "limited" and "ltd.", "group", and "international" and words that are too general such as "seafood" and "petroleum". Companies with one-word names are the most likely to collect informative Google SVI because for these companies, the Google SVI data have less than 5% occurrence of zero values. However, some one-word companies did not return any raw SVI due to insufficient search volumes when using their name as a search word so we use company tickers for these companies instead. For companies with names that contain more than one word, we checked and compared the words separately and chose the word that had lesser occurrences of zero values. We tested using the complete name of the company as the search word, although this often led to data that consisted of more than a half of zero values. Thus we opted to omit them. GT currently differentiates search words into two: (1) search terms, which show matches for all terms in the language the query was made; or (2) topics that are a group of terms that share the same concept in any language. Thus, we ended up with two raw SVIs based on the search term (henceforth *st*) and the business term for topics (henceforth *bt*).

GT provides search volume information according to a specific geographic location. Previous research by Preis et al. (2013) indicates that data filtered according to geographic location can better explain movements in the specific geographic location. Their research focused on the Dow Jones Industrial Average, one of the indexes based on the US stock market. Following their example, we filtered our data geographic location to Norway.

GT also filters information through the following categories: (1) Arts & Entertainment; (2) Autos & Vehicles; (3) Beauty & Fitness; (4) Books & Literature; (5) Business & Industrial; (6) Computer & Electronics; (7) Finance; (8) Food & Drink; (9) Games; (10) Health; (11) Hobbies & Leisure; (12) Home & Garden; (13) Internet & Telecom; (14) Jobs & Education; (15) Law & Government; (16) News; (17) Online Communities; (18) People& Society; (19) Pets & Animals; (20) Real Estate; (21) Reference; (22) Science; (23) Shopping; (24) Sports; and (25) Travel. The default filter is set to "All Categories". We checked our *st* and *bt* using the finance filter, although it yielded a dataset that mostly contained 0 values; thus we opted to omit them. This confirms the results from Bijl et al. (2016) that the finance filter does not provide any improvement over the unfiltered searches in terms of predicting stock returns.

Finally, GT also filters its data according to which channel a search was made: Web, YouTube, News, Photos, and Google Shopping. From these channels, web searches yielded more variations in raw SVI for most of the companies; thus we only focused on obtaining web searches for our search term and business term.

Raw SVI_{st} and raw SVI_{bt} are then used to compute abnormal SVI (henceforth ASVI). Raw SVI cannot be used in the analysis directly, because its value depends on the time period of downloaded data. For example, value of SVI for the first week in January 2015 depends on whether we download data from 2013 to 2015, or from 2014 to 2016. Som standardization relatively to its past history is therefore necessary. We compute for $ASVI_t$ using the two methods discussed by Bijl et al. (2016) and Da et al. (2011).

The first method, denoted as $ASVI_t^B$, follows the formula used by Bijl et al. (2016), where the average of the past 52 weeks is subtracted from the weekly raw SVI and by dividing their difference from the standard deviation of the previous year

$$ASVI_t^B = \frac{SVI_t - \frac{1}{52}\sum_{i=1}^{52} SVI_{t-i}}{\sigma_{SVI,t}} \tag{1}$$

where SVI_t can either be SVI_{st} or SVI_{bt}, and $\sigma_{SVI,t}$ is the standard deviation of the SVI for the past 52 weeks.

The second method, denoted as $ASVI_t^D$, follows the formula used by Da et al. (2011), where the log of the weekly raw SVI is subtracted from the log of the median SVI in the past 52 weeks:

$$ASVI_t^D = \log SVI_t - \log[Median(SVI_{t-1}, \ldots, SVI_{t-52}).] \tag{2}$$

We also study these standardizations over the past 8 and 26 week time horizons as a robustness check.

Figure 1 illustrates the raw (before standardization) SVI for three randomly selected companies, as well as the SVI standardized in two different ways. We can observe that the standardization indeed makes SVI data more comparable across companies. The main difference between the standardization of Da et al. (2011) and Bijl et al. (2016) is that the standardization of Da et al. (2011) sometimes results in very low values due to its logarithmic form. This is inconvenient, because results in regression analysis would depend too much on these few observations. Therefore, we chose to use the standardization of Bijl et al. (2016) as the main standardization. However, we repeat the calculations with various standardizations and find that all the standardizations lead to almost identical results.

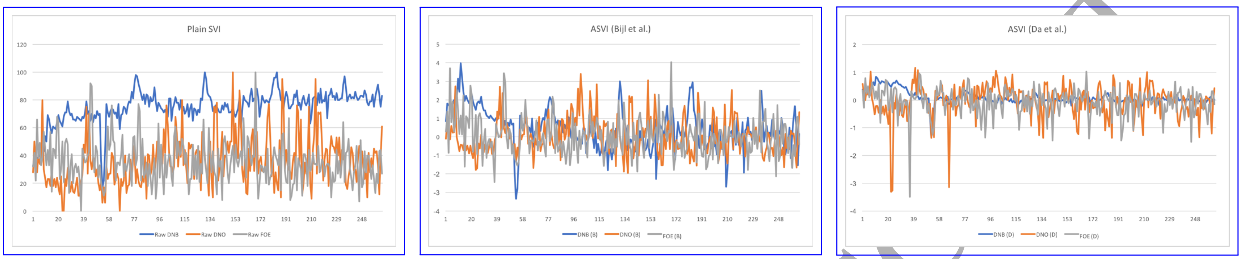

Fig. 1. Comparison of search volumes for three companies before and after standardization: Raw Google SVI for companies with DNB, DNO, and FOE tickers (left), ASVI for companies with DNB, DNO, and FOE tickers, computed using the formula used by Bijl et al. (2016) (middle), ASVI for companies with DNB, DNO, and FOE tickers, computed using the formula used by Da et al. (2011) (right).

2.2. *Stock Market Data*

Oslo Børs is Norway's central marketplace for listing and trading financial instruments and has five different marketplaces: Oslo Børs, Oslo Axess, Merkur Market, Nordic ABM and Oslo Connect. These five marketplaces offer listing and trading in equities, equity certificates, ETPs, fixed income products, and derivatives products.

Oslo Børs has an index called the OBX, which consists of the 25 most traded securities based on a six-month turnover. Within our specific five-year period, a total of 40 different companies have been included in the OBX index. Four companies were excluded in that span, which preliminary narrowed our list down to 36. We obtained historical data for the companies that belong to OBX from Yahoo! Finance. Due to missing data for some of the companies in our list, our final sample consists of 28 companies.

Our dataset consists of 261 weeks. Each weekly return is calculated from adjusted closing prices on Mondays. Some Mondays in our dataset still had missing data due to Norway-specific holidays and non-trading days. For these instances, we then used the reported stock price from the closest previous trading day.

Yahoo's adjusted closed price already adjusts for dividend payments and splits, thus we compute the raw returns directly from the prices

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

where r_t is the raw log return and P_t is the adjusted stock price for week t and P_{t-1} is the adjusted stock price from the previous week.

Further, we calculate abnormal returns from a 5-factor asset pricing model. For our regression model, we adjust the return r_t with the factors from the Fama and French asset pricing model to compute abnormal return. We acquired our asset pricing data at OSE from Norwegian Financial Data. Based on previous research by Odegaard (2017), we use the following pricing factors in our computation: the market return, the size factor (small-minus-big, SMB), the value factor (high-minus-low, HML) suggested by Fama and French (1993), the momentum factor (PR1YR) suggested by Carhart (1997), and the liquidity factor (LIQ) (Pástor and Stambaugh, 2003; Næs et al., 2009). The model is specified as follows:

$$r - r_f = \alpha + \beta_m(r_m - r_f) + \beta_{smb}SMB + \beta_{hml}HML + \beta_{pr1yr}PR1YR + \beta_{liq}LIQ + \epsilon \tag{4}$$

where r_f is the risk-free rate and βs are the pricing factor loadings. We estimate the beta coefficients from a 1-year rolling-window regression. The abnormal return AR_t is calculated as the difference between the actual return and the expected return based on the 5-factor model:

$$AR = r - r_f - \hat{\beta}_m(r_m - r_f) - \hat{\beta}_{smb}SMB - \hat{\beta}_{hml}HML - \hat{\beta}_{pr1yr}PR1YR + \hat{\beta}_{liq}LIQ. \tag{5}$$

The pricing factors and the risk-free rate were not available at a weekly frequency. We thus converted daily to weekly data by compounding the returns from Monday to Monday. To address the missing values at non-trading days, we followed a similar procedure as for stock returns.

Furthermore, we construct the volume variable. First, we convert daily trading volume TV_t^D to weekly trading volume TV_t by calculating the average trading volume

$$TV_t = \frac{1}{|S_t|}\sum_{i\in S_t} TV_t^D \tag{6}$$

where S_t is a set of all trading days during a given week t and $|S_t|$ is the number of the trading days in a given week.

We then calculate the abnormal trading volume ATV_t. Based on the formula used by Bijl et al. (2016), ATV_t is scaled by subtracting the mean of the past 52 weeks from the weekly trading volume and dividing their standard deviation of the previous year

$$AVT_t = \frac{TV_t - \frac{1}{52}\sum_{i=1}^{52} TV_{t-i}}{\sigma_{TV,t}} \tag{7}$$

where σ_{TV} is the standard deviation of the volume for the past 52 weeks.

The last financial variable we consider is volatility. Volatility is a popular measure to evaluate how stock returns vary over time. Previous studies have examined the effect of volatility on future stock returns and indeed find a positive relationship (French et al., 1987; Banerjee et al., 2007; Bollerslev et al., 2009). Therefore, it is necessary to include volatility as a control variable in our regression model explaining returns and volume, and also as a measure for market activity. We measure volatility utilizing the Garman and Klass (1980) volatility estimator adjusted for the opening jump, as discussed in Molnár (2012). The measure exploits information in open ($open_t$), high ($high$), low (low_t), close ($close_t$) and adjusted close prices ($radj_t$) during a trading day t to calculate the variance for that day in the following way:

$$Variance_t = \frac{1}{2}(h_t - l_t)^2 - (2\log 2 - 1)c_t^2 + jadj_t^2 \tag{8}$$

where

$$\begin{aligned}
c_t &= \log(close_t) - \log(open_t),\\
l_t &= \log(low_t) - \log(open_t),\\
h_t &= \log(high_t) - \log(open_t),\\
j_t &= \log(open_t) - \log(close_{t-1}),\\
r_t &= \log(close_t) - \log(close_{t-1}),\\
jadj_t &= j_t\frac{radj_t}{r_t}.
\end{aligned}$$

Finally, we calculate the weekly volatility as a square root of average daily variance

$$Volatility_t = \sqrt{\frac{1}{|S_t|}\sum_{i\in S_t} Variance_t} \tag{9}$$

2.3. Summary Statistics

In Table 1 we present the summary statistics for the variables we generated from our dataset. The abnormal SVI based on the search term or business term is calculated using Bijl et al. (2016) formula with the 52-week time horizon

Table 1: **Descriptive statistics for all variables.**

	N	Mean	St.dev.	Min	Max	Skewness	Kurtosis
Abnormal return	7308	-0.0005	0.092	-2.150	3.779	10.024	492.35
Abnormal volume	7308	0.0564	1.175	-2.507	6.967	1.481	3.19
Volatility	7308	0.0273	0.050	0.003	2.019	24.091	757.26
$ASVI_{st}$	7308	0.0439	1.027	-4.422	6.317	0.572	1.62
$ASVI_{bt}$	7308	-0.0360	1.000	-5.109	6.702	0.800	2.93

Table 2: **Correlation matrix for all variables.**

	Abn. return	Abn. volume	Volatility	$ASVI_{st}$	$ASVI_{bt}$
Abnormal return	1	0.00	0.19	0.01	-0.02
Abnormal volume	0.00	1	0.17	0.09	0.06
Volatility	0.19	0.17	1	0.02	0.02
$ASVI_{st}$	0.01	0.09	0.02	1	0.50
$ASVI_{bt}$	-0.02	0.06	0.02	0.50	1

discussed in section 2.1. Abnormal returns are calculated from the 5-factor pricing model discussed in section 2.2. Volatility is calculated using the weekly Garman-Klass jump adjusted estimator. Abnormal volume is calculated using the same standardization as the ASVI.

Next, we present the correlation between the variables in Table 2. We can observe the correlation across the variables is generally quite low. Notably, the correlation of ASVI based on the search term and ASVI based on the business term is 0.5, which means that both variables share some dependence as the search terms are matched to the exact word used in a search activity while the business terms are the general topics consisting of different search terms and grouped according to Google's algorithm.

3. Methodology

We investigate whether abnormal search volume index can explain or predict return, volatility, and trading volume utilizing panel data regressions. In descriptive regressions, the ASVI variable is contemporary with the dependent variable. In predictive regressions we use a lagged ASVI variable to investigate whether past ASVI can be useful in predicting future stock returns, volatility, and trading volume. Specific regressions are presented below.

In the descriptive model of stock returns we regress abnormal stock return against the ASVI and the set of control variables presented in section 2.2. This allows us to isolate the impact of ASVI to that of the control variables. This leads to the following regression model

$$AR_{t,i} = \alpha_i + \beta_1 AR_{t-1,i} + \beta_2 ASVI_{t,i} + \beta_3 Volatility_{t,i} + \beta_4 ATV_{t,i} + \epsilon_{t,i} \tag{10}$$

where $AR_{t,i}$ is the abnormal return at time t for firm i, βs are the regression coefficients for the lagged abnormal return, Google search volume index, volatility, and trading volume.

A descriptive model of trading volume is motivated by the results in Da et al. (2011) on whether ASVI can be used as a proxy to capture investor attention. The weekly trading volume is used as a dependent variable to see if the changes in search interest explain the changes in trading volume. We also include volatility, return, and lagged trading volume as control variables. This results in our second regression model

$$ATV_{t,i} = \alpha_i + \beta_1 ATV_{t-1,i} + \beta_2 ASVI_{t,i} + \beta_3 Volatility_{t,i} + \beta_4 AR_t + \epsilon_{t,i} \tag{11}$$

where $ATV_{t,i}$ is the abnormal volume at time t for firm i, βs are the regression coefficients for lagged trading volume, abnormal Google search volume index, volatility, and abnormal returns.

Next, we investigate whether there is a contemporary relationship between ASVI and volatility. We estimate the third descriptive model

$$Volatility_{t,i} = \alpha_i + \beta_1 Volatility_{t-1,i} + \beta_2 ASVI_{t,i} + \beta_3 ATV_{t,i} + \beta_4 AR_{t,i} + \epsilon_{t,i} \tag{12}$$

where $Volatility_{t,i}$ is the return volatility at time t for firm i, βs are the regression coefficients for lagged volatility, abnormal SVI, abnormal trading volume, and abnormal returns.

Predictive models are specified in a very similar way. However, in the predictive models we exploit only past information to predict future values. Therefore, there are only lagged variables used as possible predictors. The models can be written in a general form

$$Y_{t,i} = \alpha_i + \beta_1 Y_{t-1,i} + \beta_2 ASVI_{t-1,i} + \beta Controls_{t-1,i} + \epsilon_{t,i} \tag{13}$$

where $Y_{t,i}$ is one of the variables we investigate (abnormal return, abnormal volume or volatility) at time t for firm i regressed on its lagged value, on the lagged value of abnormal returns and on the lagged values of other considered set of variables (e.g. controls for abnormal return are abnormal volume and volatility).

In all regressions we exploit panel data and consider the firm fixed effexts indicated by index i at the intercept coefficient α.

4. Results

To assess the significance of Google searches for explaining and predicting abnormal returns we employ panel data regression models with fixed and random effects. The Hausman test always supports the fixed-effect model when these two models are compared. Therefore, only the results for the panel data regression with fixed effects are presented. Breusch-Godfrey and Breusch-Pagan tests were conducted to check for autocorrelation and heteroscedasticity. In general, we detected autocorrelation and heteroscedasticity in our dataset and consequently used the Arellano method to control them (Arellano, 1987). Hence, the results in the tables are presented with robust standard errors.

The results presented in this section are based on Google searches that are standardized relative to their previous values over the last 52 weeks, as suggested by Bijl et al. (2016). In the next section, several robustness checks are investigated, in particular, the impact of various types and time horizons for the standardization of Google searches, the impact of using the business term, and alternative models for volatility and volume, see Section 5.

Table 3: **Regression results on returns when ASVI is calculated from search term.** Columns (1)–(4) report results from a single regression to explain returns by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Return_t									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Return_{t-1}	-0.029				-0.046	Return_{t-1}				-0.022
	(0.047)				(0.058)					(0.036)
ASVI_t		0.001			0.0005	ASVI_{t-1}	0.002			0.002
		(0.0003)			(0.001)		(0.001)			(0.001)
Volatility_t			0.383		0.382	Volatility_{t-1}		-0.072		-0.069
			(0.412)		(0.426)			(0.088)		(0.072)
Volume_t				0.0003	-0.002	Volume_{t-1}			0.001	0.001
				(0.001)	(0.004)				(0.001)	(0.0009)
R^2	0.001	0.00003	0.041	0.00002	0.042		0.0005	0.002	0.0001	0.003
Adjusted R^2	-0.003	-0.004	0.038	-0.004	0.038		-0.003	-0.002	-0.004	-0.002

First, the results for models that aim to explain the abnormal returns are shown. Table 3 summarizes the results for both the descriptive and predictive models for returns. Columns (1) - (7) display the results of a univariate analysis. Neither ASVI nor individual control variables are significant in the regression analysis. The same results can be seen in the multivariate descriptive model, Column (8), and the multivariate predictive model, Column (9). Moreover, all the regressions exhibit very low values of R^2. Therefore, the search volume can neither explain the dynamics of OBX's returns nor predict its movement. Da et al. (2011) and Bijl et al. (2016) find that search volume can predict returns for up to two weeks with subsequent reversal for the US stock market. However, since we are investigating the Norwegian market, which is significantly smaller, our dataset is limited to 28 companies. As a result, our conclusion is that no relation between Google searches and stock returns in the Norwegian stock market exists or it is too weak to be detected given the size of the data sample.

Second, we explore the drivers of movements in the trading volume. Table 4 reports regression results with the volume as a dependent variable. It shows that the ASVI variable, no matter whether contemporaneous or lagged, is significant in explaining volume dynamics. The coefficient of the ASVI variable remains significant at the 99% confidence level even when the regression is augmented with other control variables. However, most of the variation in abnormal trading volume can be explained by the abnormal trading volume from the previous week. The observation that search volume can both explain and predict trading volume signifies that the investor's sentiment and attention for companies trading in the OBX are captured by the Google Search Volume Index.

Finally, Table 5 displays the results for volatility as the dependent variable. A contemporaneous value of ASVI is significant at the 90% confidence level in the initial regression with lagged volatility only. However, when regressed along with contemporaneous values of other control variables trading volume and returns, SVI becomes insignificant. In accordance with our expectations, the contemporaneous volume is significantly correlated with volatility both in the univariate and multivariate model. On the contrary, lagged ASVI remains significant at 95% confidence level, whether regressed only with lagged volatility or with other control variables (which also do not have significant predictive power). Therefore, an explanatory relationship between the current week's search activity with stock price volatility does not seem to exist. However, the search activity provides useful information about future stock price volatility in the subsequent week.

We sum up our results with the conclusion that Google searches can tell us even more about future trading activity for the Norwegian stock market (represented by volatility and volume) than they tell us about current trading activity.

Table 4: **Regression results on volume when ASVI is calculated from search term.** Columns (1)–(4) report results from a single regression to explain volume by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Volume_t									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Volume_{t-1}	0.577***	0.575***	0.569***	0.577***	0.566***	Volume_{t-1}	0.567***	0.580***	0.577***	0.569***
	(0.010)	(0.016)	(0.016)	(0.016)	(0.016)		(0.016)	(0.016)	(0.016)	(0.016)
ASVI_t		0.075***			0.072***	ASVI_{t-1}	0.129***			0.129***
		(0.014)			(0.015)		(0.017)			(0.017)
Volatility_t			2.332**		2.385*	Volatility_{t-1}		-0.331		-0.339
			(0.878)		(0.965)			(0.377)		(0.391)
Return_t				0.008	-0.251	Return_{t-1}			-0.117	-0.088
				(0.279)	(0.123)				(0.097)	(0.119)
R^2	0.332	0.336	0.342	0.332	0.346		0.345	0.332	0.332	0.345
Adjusted R^2	0.330	0.334	0.339	0.329	0.343		0.342	0.330	0.330	0.342

5. Robustness checks

In this section, we evaluate the robustness of our results with respect to several model alternatives. First, we study whether our results are robust with respect to various standardizations of the Google search variable. Second, we

Table 5: **Regression results on volatility when ASVI is calculated from search term.** Columns (1)–(4) report results from a single regression to explain volatility by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Volatility$_t$									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Volatility$_{t-1}$	0.346***	0.345***	0.337***	0.354***	0.345***	Volatility$_{t-1}$	0.344***	0.340***	0.343***	0.336***
	(0.091)	(0.091)	(0.093)	(0.088)	(0.091)		(0.091)	(0.094)	(0.084)	(0.088)
ASVI$_t$		0.001*			0.001	ASVI$_{t-1}$	0.003**			0.003**
		(0.0001)			(0.0001)		(0.0002)			(0.0002)
Volume$_t$			0.005***		0.005***	Volume$_{t-1}$		0.002		0.001
			(0.001)		(0.001)			(0.001)		(0.001)
Return$_t$				0.114	0.113	Return$_{t-1}$			0.008	0.008
				(0.108)	(0.109)				(0.053)	(0.052)
R^2	0.120	0.120	0.135	0.165	0.180		0.123	0.121	0.120	0.125
Adjusted R^2	0.116	0.117	0.132	0.161	0.176		0.120	0.118	0.116	0.121

Table 6: **Correlation matrix for ASVI using different time window for normalization.** ASVI computed using Bijl et al. (2016) formula is denoted as ASVI-B, Column (1)–(3). ASVI computed using Da et al. (2011) formula denoted as ASVI-D, Column (4)–(6).

	ASVI-B 8-week	ASVI-B 26-week	ASVI-B 52-week	ASVI-D 8-week	ASVI-D 26-week	ASVI-D 52-week
ASVI-B 8-week	1	0.86	0.80	0.70	0.66	0.64
ASVI-B 26-week	0.86	1	0.95	0.67	0.74	0.73
ASVI-B 52-week	0.80	0.95	1	0.66	0.74	0.76
ASVI-D 8-week	0.70	0.67	0.66	1	0.94	0.92
ASVI-D 26-week	0.66	0.74	0.74	0.94	1	0.98
ASVI-D 52-week	0.64	0.73	0.76	0.92	0.98	1

investigate how sensitive our results are when using Google search activity based on a business term instead of a search term. Finally, since volatility and trading volume are persistent variables, which can be explained mostly by their past values, we also study the alternative specifications for volume and volatility equations.

5.1. *Various standardizations of Google searches*

This subsection presents the regression results for different ASVI standardizations. As previously mentioned in section 2.1, we used two methods to calculate the abnormal SVI based on either Bijl et al. (2016) or Da et al. (2011). We also employed three different time horizons for our calculations: past 8 weeks, 26 weeks and 52 weeks.

In accordance with our expectations, the correlation among ASVIs with the same type of the standardization, but using a different time horizon, is very high (Table 6). The correlation across ASVIs based on different standardizations are also quite high, since the source data for computation is the same and both standardizations aim to capture the deviation of the SVI from its normal level.

Table 7, Table 8, and Table 9 present the explanatory and predictive power of the ASVI's on returns, trading volume, and volatility with and without control variables. For the sake of brevity, the tables only show the estimated coefficients (with significance denoted by asterisks) and R^2 values. It can be clearly seen that all the conclusions remain the same, no matter which standardization is used.

Table 7: **Sensitivity to ASVI standardization: Returns as the dependent variable.** The results with the standardization over last 8, 26 and 52 weeks are reported, based on either Da et al. (2011) (Panel A) or Bijl et al. (2016) (Panel B). For each standardization, univariate regressions with contemporaneous or lagged Google search activity are reported. Further, the multivariate regression with all variables is displayed, first the full descriptive model with the contemporaneous independent variables, and second the predictive model with lagged values. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Standardization based on Da et al. (2011)

Dependent Variable: $Return_t$												
	Explanatory models							Predictive models				
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks
$Return_{t-1}$		-0.046		-0.046		-0.046	$Return_{t-1}$		-0.021		-0.021		-0.021
$ASVI_t$	-0.004	-0.002	-0.003	-0.001	-0.003	-0.001	$ASVI_{t-1}$	0.004	0.004	0.005	0.005	0.005	0.004
$Volatility_t$		0.382		0.382		0.382	$Volatility_{t-1}$		-0.068		-0.068		-0.069
$Volume_t$		-0.002		-0.002		-0.002	$Volume_{t-1}$		0.001		0.001		0.001
R^2	0.000	0.042	0.000	0.042	0.000	0.042	R^2	0.001	0.003	0.001	0.003	0.001	0.003

Panel B: Standardization based on Bijl et al. (2016)

Dependent Variable: $Return_t$												
	Explanatory models							Predictive models				
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks
$Return_{t-1}$		-0.046		-0.046		-0.046	$Return_{t-1}$		-0.021		-0.022		-0.022
$ASVI_t$	-0.001	-0.001	0.000	0.000	0.001	0.000	$ASVI_{t-1}$	0.002	0.002	0.002	0.002	0.002	0.002
$Volatility_t$		0.382		0.382		0.382	$Volatility_{t-1}$		-0.069		-0.069		-0.069
$Volume_t$		-0.002		-0.002		-0.002	$Volume_{t-1}$		0.001		0.001		0.001
R^2	0.000	0.042	0.000	0.042	0.000	0.042	R^2	0.000	0.003	0.001	0.003	0.000	0.003

Table 8: **Sensitivity to ASVI standardization: Volume as the dependent variable.** The results with the standardization over last 8, 26 and 52 weeks are reported, based on either Da et al. (2011) (Panel A) or Bijl et al. (2016) (Panel B). For each standardization, initial regressions with contemporaneous or lagged Google search activity and volume are reported. Further, the multivariate regression with all variables is displayed, first the full descriptive model with the contemporaneous independent variables, and second the predictive model with lagged values. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Standardization based on Da et al. (2011)

Dependent Variable: $Volume_t$												
	Explanatory models							Predictive models				
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks
$Volume_{t-1}$	0.576***	0.567***	0.573***	0.564***	0.572***	0.564***	$Volume_{t-1}$	0.570***	0.571***	0.567***	0.568***	0.566***	0.568***
$ASVI_t$	0.151***	0.150***	0.161***	0.159***	0.162***	0.160***	$ASVI_{t-1}$	0.245***	0.244***	0.234***	0.233***	0.230***	0.230***
$Volatility_t$		2.420*		2.412*		2.403*	$Volatility_{t-1}$		-0.278		-0.287		-0.298
$Return_t$		-0.240		-0.241		-0.240	$Return_{t-1}$		-0.059		-0.063		-0.062
R^2	0.336	0.346	0.337	0.347	0.337	0.347	R^2	0.342	0.342	0.342	0.342	0.342	0.342

Panel B: Standardization based on Bijl et al. (2016)

Dependent Variable: $Volume_t$												
	Explanatory models							Predictive models				
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks
$Volume_{t-1}$	0.578***	0.570***	0.575***	0.567***	0.575***	0.566***	$Volume_{t-1}$	0.571***	0.573***	0.567***	0.569***	0.567***	0.569***
$ASVI_t$	0.069***	0.067***	0.077**	0.074***	0.075***	0.072***	$ASVI_{t-1}$	0.148***	0.148***	0.131***	0.132***	0.129***	0.129***
$Volatility_t$		2.402*		2.385*		2.385*	$Volatility_{t-1}$		-0.320		-0.337		-0.339
$Return_t$		-0.243		-0.249		-0.251	$Return_{t-1}$		-0.071		-0.083		-0.088
R^2	0.336	0.345	0.337	0.347	0.336	0.346	R^2	0.348	0.348	0.346	0.346	0.345	0.345

Table 9: **Sensitivity to ASVI standardization: Volatility as the dependent variable.** The results with the standardization over last 8, 26 and 52 weeks are reported, based on either Da et al. (2011) (Panel A) or Bijl et al. (2016) (Panel B). For each standardization, initial regressions with contemporaneous or lagged Google search activity and lagged volatility are reported. Further, the multivariate regression with all variables is displayed, first the full descriptive model with the contemporaneous independent variables, and second the predictive model with lagged values. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Standardization based on Da et al. (2011)

Dependent Variable: Volatility_t													
	Explanatory models							Predictive models					
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks	
Volatility_{t-1}	0.346***	0.345***	0.346***	0.345***	0.345***	0.345***	Volatility_{t-1}	0.346***	0.337***	0.345***	0.337***	0.345***	0.337***
ASVI_t	0.000	-0.001	0.001	-0.001	0.001	-0.0004	ASVI_{t-1}	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
Volume_t		0.005***		0.005***		0.005***	Volume_{t-1}		0.001		0.001		0.001
Return_t		0.113		0.113		0.113	Return_{t-1}		0.009		0.009		0.009
R^2	0.120	0.179	0.120	0.179	0.120	0.179	R^2	0.122	0.123	0.122	0.124	0.122	0.124

Panel B: Standardization based on Bijl et al. (2016)

Dependent Variable: Volatility_t													
	Explanatory models							Predictive models					
	8 weeks		26 weeks		52 weeks			8 weeks		26 weeks		52 weeks	
Volatility_{t-1}	0.346***	0.345***	0.345***	0.345***	0.345***	0.345***	Volatility_{t-1}	0.345***	0.337***	0.344***	0.336***	0.344***	0.336***
ASVI_t	0.001	0.000	0.001	0.000	0.001*	0.001	ASVI_{t-1}	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
Volume_t		0.005***		0.005***		0.005***	Volume_{t-1}		0.002		0.001		0.001
Return_t		0.113		0.113		0.113	Return_{t-1}		0.009		0.008		0.008
R^2	0.120	0.179	0.120	0.180	0.120	0.180	R^2	0.122	0.124	0.123	0.124	0.123	0.125

5.2. *Google searches defined as a business term*

In this subsection, we estimated the same models as in the previous section, with the difference that Google search words are now based on a business term instead of a search term. The results are presented in Table 10, Table 11, and Table 12. The results for the business terms (*bt*) were similar to those for the search terms (*st*) reported in section 4. However, models based on a business term have less explanatory power in comparison to models based on a search term. Therefore, we do not find any advantage of using a business term and recommend to use a simple search term.

6. Conclusion

The aim of this paper is to investigate whether Google search activity can explain and predict activity in the Norwegian stock market, in particular, the dynamics of stock returns, trading volume, and volatility.

Regarding the stock returns, we can find neither a contemporary relationship nor a predictive ability of Google searches on stock returns. This is different from previous findings from the US market (Da et al., 2011; Bijl et al., 2016). However, this result does not necessarily mean that such a relationship does not exist in the Norwegian stock market. This could be caused by the smaller size of our sample – the number of stocks in the Norwegian stock market is much less than the number of stocks in the US stock market.

On the other hand, the Google searches can both explain and predict trading volume. This indicates that investors in the Norwegian stock market use information from Google along with other information channels in making investment decisions, which confirms the intuition from Da et al. (2011). Finally, Google search activity does not have contemporary relation with volatility, but it can predict future volatility. Altogether, Google searches are not only related to, but can also predict trading activity measured by volatility and trading volume. Surprisingly, the predictive power of Google searches is even stronger than their contemporary explanatory power for both volatility and trading volume.

The results that Google searches can predict trading volume and volatility, but not returns, are in accordance with market efficiency. If Google searches would predict returns in Norwegian markets, investors could easily benefit from this although such profit opportunities do not arise from the predictability of trading volume and volatility.

In addition to our main findings, we also conclude that general Google searches specified as a search term are more related to the stock market than more specific Google searches specified as a business term. Moreover, various

Table 10: **Regression results on returns when ASVI is calculated from business term.** Columns (1)–(4) report results from a single regression to explain returns by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Return_t									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Return_{t-1}	-0.029				-0.046	Return_{t-1}				-0.022
	(0.047)				(0.058)					(0.036)
ASVI_t		-0.001			-0.002	ASVI_{t-1}	-0.000			-0.000
		(0.001)			(0.001)		(0.008)			(0.000)
Volatility_t			0.383		0.382	Volatility_{t-1}		-0.072		-0.069
			(0.412)		(0.426)			(0.088)		(0.071)
Volume_t				0.000	-0.002	Volume_{t-1}			0.001	0.001
				(0.001)	(0.004)				(0.001)	(0.009)
R^2	0.001	0.000	0.041	0.000	0.042		0.000	0.002	0.000	0.002
Adjusted R^2	-0.003	-0.004	0.038	-0.004	0.038		-0.004	-0.002	-0.004	-0.002

Table 11: **Regression results on volume when ASVI is calculated from business term.** Columns (1)–(4) report results from a single regression to explain volume by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Volume_t									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Volume_{t-1}	0.577***	0.576***	0.569***	0.577***	0.568***	Volume_{t-1}	0.571***	0.580***	0.577***	0.573***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)		(0.016)	(0.016)	(0.016)	(0.016)
ASVI_t		0.052**			0.050**	ASVI_{t-1}	0.126***			0.126***
		(0.017)			(0.017)		(0.018)			(0.018)
Volatility_t			2.332**		2.400*	Volatility_{t-1}		-0.331		-0.342
			(0.878)		(0.967)			(0.377)		(0.382)
Return_t				0.008	-0.237*	Return_{t-1}			-0.117	-0.058
				(0.279)	(0.531)				(0.097)	(0.117)
R^2	0.332	0.334	0.342	0.332	0.344		0.344	0.332	0.332	0.344
Adjusted R^2	0.330	0.331	0.339	0.329	0.341		0.341	0.330	0.330	0.341

Table 12: **Regression results on volatility when ASVI is calculated from business term.** Columns (1)–(4) report results from a single regression to explain volatility by various independent variables. Columns (5) corresponds to multiple regressions. Columns (6)–(9) display the corresponding results for predictive models. Robust standard errors are reported in parentheses. The sample period covers weekly data from 2012 to 2017. The symbols ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Volatility$_t$									
	Explanatory models						Predictive models			
	(1)	(2)	(3)	(4)	(5)		(6)	(7)	(8)	(9)
Volatility$_{t-1}$	0.346***	0.346***	0.337***	0.354***	0.345***	Volatility$_{t-1}$	0.345***	0.340***	0.343***	0.336***
	(0.091)	(0.091)	(0.093)	(0.088)	(0.091)		(0.091)	(0.094)	(0.084)	(0.088)
ASVI$_t$		0.001*			0.001	ASVI$_{t-1}$	0.002*			0.002**
		(0.0001)			(0.0001)		(0.0002)			(0.0002)
Volume$_t$			0.005***		0.005***	Volume$_{t-1}$		0.002		0.002
			(0.001)		(0.001)			(0.001)		(0.001)
Return$_t$				0.114	0.113	Return$_{t-1}$			0.008	0.009
				(0.108)	(0.109)				(0.053)	(0.052)
R^2	0.120	0.120	0.135	0.165	0.180		0.121	0.121	0.120	0.123
Adjusted R^2	0.116	0.117	0.132	0.161	0.176		0.118	0.118	0.116	0.119

ways of standardization of the Google search variable lead to the same conclusions.

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References

References

Aouadi, A., Arouri, M., Teulon, F., 2013. Investor attention and stock market activity: Evidence from France. Economic Modelling 35, 674–681.
Arellano, M., 1987. Computing robust standard errors for within-groups estimators. Oxford Bulletin of Economics and Statistics 49, 431–434.
Banerjee, P. S., Doran, J. S., Peterson, D. R., 2007. Implied volatility and future portfolio returns. Journal of Banking & Finance 31, 3183–3199.
Bank, M., Larch, M., Peter, G., 2011. Google search volume and its influence on liquidity and returns of german stocks. Financial Markets and Portfolio Management 25, 239–264.
Bijl, L., Kringhaug, G., Molnár, P., Sandvik, E., 2016. Google searches and stock returns. International Review of Financial Analysis 45, 150–156.
Bollerslev, T., Tauchen, G., Zhou, H., 2009. Expected stock returns and variance risk premia. The Review of Financial Studies 22, 4463–4492.
Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52, 57–82.
Challet, D., Ayed, A. B. H., 2014. Do Google Trend data contain more predictability than price returns?, Working paper.
Choi, H., Varian, H., 2012. Predicting the present with Google Trends. Economic Record 88, 2–9.
Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance 66, 1461–1499.
Da, Z., Engelberg, J., Gao, P., 2014. The sum of all fears investor sentiment and asset prices. The Review of Financial Studies 28, 1–32.
Dimpfl, T., Jank, S., 2016. Can internet search queries help to predict stock market volatility? European Financial Management 22, 171–192.
Eysenbach, G., 2006. Infodemiology: tracking flu-related searches on the web for syndromic surveillance. In: *AMIA Annual Symposium Proceedings*, American Medical Informatics Association, vol. 2006, p. 244.
Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Fink, C., Johann, T., 2014. May I have your attention, please: The market microstructure of investor attention, Working paper.
French, K. R., Schwert, G. W., Stambaugh, R. F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.
Garman, M. B., Klass, M. J., 1980. On the estimation of security price volatilities from historical data. Journal of Business 53, 67–78.
Ginsberg, J., Mohebbi, M. H., Patel, R. S., Brammer, L., Smolinski, M. S., Brilliant, L., 2009. Detecting influenza epidemics using search engine query data. Nature 457, 1012–1014.
Goddard, J., Kita, A., Wang, Q., 2015. Investor attention and FX market volatility. Journal of International Financial Markets, Institutions and Money 38, 79–96.
Gwilym, O. A., Hasan, I., Wang, Q., Xie, R., 2016. In search of concepts: The effects of speculative demand on stock returns. European Financial Management 22, 427–449.
Harford, T., 2017. Just google it: The student project that changed the world. Accesible online http://www.bbc.com/news/business-39129619.

Joseph, K., Wintoki, M. B., Zhang, Z., 2011. Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. International Journal of Forecasting 27, 1116–1127.

Molnár, P., 2012. Properties of range-based volatility estimators. International Review of Financial Analysis 23, 20–29.

Molnár, P., Bašta, M., 2017. Google searches and gasoline prices. In: *European Energy Market (EEM), 2017 14th International Conference on the*, IEEE, pp. 1–5.

Næs, R., Skjeltorp, J., Ødegaard, B. A., et al., 2009. What factors affect the Oslo Stock Exchange. Norges Bank (Central Bank of Norway), Working Paper .

Odegaard, B. A., 2017. Empirics of the Oslo Stock Exchange: Asset pricing results 1980–2016. Tech. rep., University of Stavanger.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Polgreen, P. M., Chen, Y., Pennock, D. M., Nelson, F. D., Weinstein, R. A., 2008. Using internet searches for influenza surveillance. Clinical infectious diseases 47, 1443–1448.

Preis, T., Moat, H. S., Stanley, H. E., 2013. Quantifying trading behavior in financial markets using Google Trends. Scientific reports 3, 1684.

Preis, T., Reith, D., Stanley, H. E., 2010. Complex dynamics of our economic life on different scales: insights from search engine query data. Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences 368, 5707–5719.

Takeda, F., Wakao, T., 2014. Google search intensity and its relationship with returns and trading volume of Japanese stocks. Pacific-Basin Finance Journal 27, 1–18.

Tantaopas, P., Padungsaksawasdi, C., Treepongkaruna, S., 2016. Attention effect via internet search intensity in Asia-Pacific stock markets. Pacific-Basin Finance Journal 38, 107–124.

Vlastakis, N., Markellos, R. N., 2012. Information demand and stock market volatility. Journal of Banking & Finance 36, 1808–1821.

Vozlyublennaia, N., 2014. Investor attention, index performance, and return predictability. Journal of Banking & Finance 41, 17–35.