UNIVERSIDAD CARLOS III DE MADRID working papers

Working Paper 13-06
Statistics and Econometrics Series 05
March 2013

Departamento de Estadística
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 91 624-98-48

Predictability of stock market activity using Google search queries

Pedro Latoeiro[1], Sofia B. Ramos[2] and Helena Veiga[3]

Abstract
This paper analyzes whether web search queries predict stock market activity in a sample of the largest European stocks. We provide evidence that i) an increase in web searches for stocks on Google engine is followed by a temporary increase in volatility and volume and a drop in cumulative returns. ii) An increase for web search queries for the market index leads to a decrease in the returns of the index as well as of the stock index futures and an increase in implied volatility. iii) Attention interacts with behavioral biases. The predictability of web searches for return and liquidity is enhanced when firm prices and market prices hit a 52-week high and diminished when the market hits a 52-week low. iv) Investors tend to process more market information than firm specific information in investment decisions, confirming limited attention theory.

Keywords: Behavioral Finance; Google Search Volume Index; Investor Attention; Predictability.

[1] Pedro Latoeiro, Instituto Universitario de Lisboa (ISCTE-IUL), Avenida das For\c cas Armadas, 1600-083 Lisboa, Portugal.
[2] Sofia B. Ramos, Business Research Center/UNIDE, Lisbon University Institute (ISCTE-IUL), Avenida das Forças Armadas, 1600-083 Lisboa, Portugal. Email: sofia.ramos@iscte.pt. *Corresponding author*.
[3] Helena Veiga, Universidad Carlos III de Madrid (Department of Statistics and Instituto Flores de Lemus), C/ Madrid 126, 28903 Getafe, Spain. BRU/UNIDE, Avenida das Forças Armadas, 1600-083 Lisboa, Portugal.

Predictability of stock market activity using Google search queries*

Pedro Latoeiro† **Sofia B. Ramos**‡ **Helena Veiga**§

ABSTRACT

This paper analyzes whether web search queries predict stock market activity in a sample of the largest European stocks. We provide evidence that i) an increase in web searches for stocks on Google engine is followed by a temporary increase in volatility and volume and a drop in cumulative returns. ii) An increase for web search queries for the market index leads to a decrease in the returns of the index as well as of the stock index futures and an increase in implied volatility. iii) Attention interacts with behavioral biases. The predictability of web searches for return and liquidity is enhanced when firm prices and market prices hit a 52-week high and diminished when the market hits a 52-week low. iv) Investors tend to process more market information than firm specific information in investment decisions, confirming limited attention theory.

JEL classification: G02

Keywords: Behavioral Finance; Google Search Volume Index; Investor Attention; Predictability.

*The authors acknowledge financial support from Fundação para a Ciência e Tecnologia PEst-OE/EGE/UI0315/2011 and from the Spanish Ministry of Education and Science, research projects ECO2012-32401 and MTM2010-17323.

†Instituto Universitario de Lisboa (ISCTE-IUL), Avenida das Forças Armadas, 1600-083 Lisboa, Portugal.

‡Instituto Universitario de Lisboa (ISCTE-IUL), BRU/UNIDE, Avenida das Forças Armadas, 1600-083 Lisboa, Portugal. Email:sofia.ramos@iscte.pt. Corresponding author.

§Universidad Carlos III de Madrid (Department of Statistics and Instituto Flores de Lemus), C/ Madrid 126, 28903 Getafe, Spain.Tel:+34916248902. Email: mhveiga@est-econ.uc3m.es.

I. Introduction

During the week that Lehman Brothers declared bankruptcy in September 2008, the volume of Google searches on "Lehman" was 24 times higher than the historical average. About a year later, in November 2009, the Dubai World sought to reschedule a debt due to accumulated losses. Demand for information on Google about "Dubai World" increased six-fold. In the following year, the leak from a British Petroleum platform caused an environmental disaster in the Gulf of Mexico. The frequency of Google searches on "BP" quintupled during this period. In London, the volume of securities traded in May 2010 was twice the average of the previous 12 months.

In this paper we investigate whether web search queries for stocks are related with investment decisions. Is the internet search for company names imbued with a trading purpose? Does it precede an investment decision? Recent works provide evidence that the number of requests submitted by users to web search engines can be used to track and, in some cases, to anticipate several social phenomena such as outbreak of influenza and other pandemic diseases (see e.g. Ginsberg et al., 2009; Carneiro and Mylonakis, 2009; Desai et al., 2012; Polgreen et al., 2008), unemployment using search queries for jobs (see e.g. Ettredge et al., 2005; Askitas and Zimmermann, 2009) or consumption decisions for cars, travel among others (see e.g. Varian and Choi, 2009; Goel et al., 2009). Searching for information on the internet is more likely to be related to an action, as it captures interest better than just looking at advertising or reading newspapers. Therefore, web search queries have great potential to anticipate behaviors or decisions.

Testing for the effects of investor attention has been a challenge due to the difficulty in measuring it accurately.[1] Recent research in finance concludes that internet search queries proxied by Google Search Volume Index (GSVI) seems to be a good measure of investor attention in a way not captured by other measures such as firm size, or extreme price movements (Da et al., 2011). More specifically, GSVI appears to be a good metric of small investor attention. *"Whose*

[1] Common proxies of investor attention have been abnormal trading (see, e.g. Barber and Odean, 2008; Chemmanur and Yan, 2009) or hitting price limits (see, e.g. Peng et al., 2012; Seasholes and Wu, 2007).

attention does SVI capture? Intuitively, people who search financial information related to a stock in Google are more likely to be individual or retail investors since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg terminals." (see Da et al., 2011, pag.1475). Using detailed information of the search engine Yahoo, Bordino et al. (2012) find that most users search only one ticker, not only within a month, but also within the whole year. The research also finds that these users do not regularly check a wide portfolio of stocks and that there is not a consistent pattern over time. The authors conclude that most users of Yahoo engine are not financial experts.

This paper investigates predictability between web search queries measured by GSVI and the market behavior of stocks of the EURO STOXX 50 index. To start the analysis, we construct four portfolios sorted according to the frequency of web search queries and we track their performance four weeks before and after portfolio formation. The results show a surge in liquidity in the week following search queries, that is reversed in the subsequent week. To illustrate the potential of a 'web search activity strategy' we compute the cumulative returns of a strategy where stocks are sorted according to the frequency of Google search queries. Every week stocks are allocated into four portfolios based on GSVI. Figure 1 shows that the cumulative returns of a portfolio long on low web search activity and short on web high search activity would provide positive returns.

Our paper makes several contributions to the literature. First, we provide evidence that web search queries lead one-week changes in stock market activity; more specifically, an increase in web search queries leads a surge in liquidity and volatility, and a drop in cumulative returns. These findings are consistent with previous evidence that finds some relation between GSVI and trading of unsophisticated investors and the short term nature of GSVI forecasts. The disposition effect can be a possible explanation to negative returns. Accordingly, after the attention level of investors is raised, investors notice many winner stocks in the portfolio and decide to sell those winners, and the selling pressure makes prices fall.

Secondly, we provide new evidence on how investors' attention interacts with investor behavioral biases. We investigate the hypothesis that if web search queries proxy for individual investor attention, then they might interact with investor behavioral bias. We analyze the case of reference prices such as 52-week high and low prices, because they are salient cues with well documented effects on investment decisions. We posit that 52-week highs and lows will enhance (or diminish) the predictability of web search queries. To analyze the effects of limited attention, we examine both firm and market 52-week highs and lows. According to this hypothesis, attention is a scarce resource and therefore constrained investors may choose to select only a few sources of salient information. Peng and Xiong (2006) model theorizes that limited investor attention leads to category-learning behavior, i.e., investors tend to process more market wide information than firm specific information. Following these results, we expect that market information enhances the predictability of web searches.

The results are supportive of 52-week highs and lows being reference prices and heightening trade in line with anchoring and investor attention theories. Moreover, the results show that the effects of GSVI as a predictor of volume are exacerbated when firm and market levels hit a 52-week high and mitigated when the stock market hits a 52-week low. In sum, our evidence suggests that investors process more market information than firm information given that the predictability of web search queries is more affected by market breakthroughs than firm breakthroughs.

Next, we analyze whether search queries for the EURO STOXX market index are able to predict returns of the index but also of the stock index futures. The results show that an increase in web searches for the index predicts a drop in the market index, but market breakthroughs do not seem to have an enhancing or diminishing effect on the predictability of web search queries. The predictability of web search queries for implied volatility is, however, changed when the market hits a 52-week high and low. We note that futures and options are mainly traded by sophisticated investors, and the reported changes of the index and of implied volatility are not anticipated by these investors, suggesting that web search activity might contain information not impounded in prices.

The findings of this paper add to the literature on investor attention. The effects of individual investor attention have not been well understood mainly due to the empirical challenge of testing. Because previous studies have relied on critical assumptions that large returns, large changes in volume or mention in the news were signs of investor attention, variables that measure investor attention more directly are a step to a richer analysis. We provide evidence that investor attention precedes stock market activity in a sample of salient stocks. Additionally, we provide novel evidence on how investor attention interacts with behavioral biases. Not least important, our results are empirically consistent with the effects of limited attention theory and investors processing more market information than firm information.[2]

The paper provides insights into small investors' behavior, and how they use information from internet to take investment decisions. Thus our conclusions are relevant for regulators and for those that assure the reliability of financial information and the protection of small investors. They indicate that attention should be given to information on the web.

II. Review of Literature

The importance of investor cognizance on asset pricing was first recognized by Merton (1987). The model assumes that each investor knows about only a subset of all available securities, which causes an imperfect portfolio diversification. In equilibrium stocks of less-known firms have to offer higher returns to compensate for the lower degree of diversification. Empirically, studies seem to concur that neglected stocks (see e.g Arbel and Strebel, 1982; Arbel et al., 1983) as well as firms with a smaller shareholder base (see e.g Bodnaruk and Ostberg, 2009; Richardson et al., 2012) offer higher returns.

Barber and Odean (2008) analyze how an increase in retail investors' attention affects stock returns. They test the proposition that individual investors are more likely to buy rather than sell those stocks that catch their attention. This happens because selling a stock requires individuals

[2]Most of the evidence has focused on investor inattention. Hirshleifer et al. (2009) show that when firms disclose earning results at the same time, it distracts investors and they underact to the information. Louis and Sun (2010) find evidence of investor inattention on Fridays to important corporate events such as merger announcements. Gilbert et al. (2012) find that investors are not attentive to the US leading economic index and that front running strategies generate abnormal profits. Schmidt (2013) uses rational attention theory to posit that when attention is scarce, investors prioritize market news over firm-specific news. As a result, stock prices incorporate less firm-specific news and returns move more synchronously.

to have already owned the stock, whereas individuals can choose from a large set of alternatives when buying. Therefore, they advocate that attention shocks lead to net buying by retail traders; in conjunction with the fact that retail traders are generally uninformed, this should lead to temporarily higher returns. They proxy investor attention by extreme returns, abnormal trading volume, news and headlines. Their findings confirm that individuals buy stocks with high volume, large price gains on the previous day, large price drops on the previous day and days with news events. They also confirm that the buying behavior of individual investors is more heavily influenced by attention than the buying behavior of professional investors.

Advertising or obtaining media coverage are common ways of attracting attention. Grullon et al. (2004) show that firms with higher advertising expenses have more liquid stocks and a larger number of investors. Due to advertising, investors' familiarity with firms increases, and shareholder base increases. Fang and Peress (2009) investigate the cross-sectional link between media coverage and expected stock returns. Without classifying news reports into positive or negative information, they show that less-covered firms exhibit higher returns, even after controlling for well-known risk factors. Kim and Meschke (2011) find that firms whose CEOs are interviewed on CNBC earn abnormal returns that mean revert within 10 days. Li et al. (2011) analyze the impact of investor attention on stocks prices of small capitalization firms that have similar tickers similar to large firms in the news (proxied by extreme returns or high trade volumes). Their hypothesis is that if an event raises investors' attention to a neglected security, the security subsequently experiences higher trade activities and current returns (and hence lower expected future returns or cost of capital). They find that subsequent to the portfolio formation, trade activity in attention stocks increases and attention portfolios yield 3.3% annualized excess return in the three weeks following their formation relative to the rest of the stocks in the same size quintile (baseline portfolio).

Yuan (2012) also explores media coverage by using front page articles about the stock market and record-breaking events of the Dow Jones index. The paper analyzes the ability of market-wide attention-grabbing events, record-breaking events of the Dow Jones index and front page articles about the stock market to predict the trading behavior of investors and market returns. The empirical results show that the impact of attention is pervasive across the market. High attention causes individual investors to reduce their stock holdings dramatically when the market level is high and to increase their stock holdings modestly when the market level is low. The aggressive selling by individual investors induces institutional investors to trade and has a negative impact on market prices, reducing market returns by 19 basis points on days following attention-grabbing events.

Recent studies explore data on internet search queries. They seem to concur for example that internet demand for information is a more reliable proxy of investor attention than headlines in news. It is uncertain whether an investor reads the news, but searching for information in the internet is clearly a direct measure of investor interest and might indicate predisposition for a trading decision. GSVI is used by Da et al. (2011) to derive a measure of investor attention and study its relationship with the commonly used measures of attention in the literature. The authors analyze a panel of weekly GSVI values for Russell 3000 stock tickers with respect to stock price activity. The results indicate that GSVI is able to capture investors' attention more efficiently than the alternative attention measures, especially in the case of less sophisticated investors. They also provide evidence that shifts in GSVI lead to temporary increases in stock prices, especially in the case of IPOs.

Bank et al. (2011) employ a data set of the German stock market and they test Amihud and Mendelson (2006) hypothesis that adding small investors to a firm investor base should improve the liquidity of its stock. They find that an increase in Google engine search queries is associated with a rise in trading activity and stock liquidity and with a reduction in asymmetric information costs due to an improvement in liquidity. Moreover, they find evidence that an increase in search volume is associated with temporarily higher future returns. This effect appears particularly strong for companies with low market capitalization. They conclude that search volume primarily proxies the attention from uninformed investors.

Smith (2012) studies whether evolution in the number of Google internet searches for particular keywords can predict volatility in the foreign currency market. He finds that data on Google searches for the keywords "economic crisis", "financial crisis" and "recession" has incremental predictive power beyond the GARCH (1,1). The number of Google internet searches for the keywords "economic crisis" and "financial crisis" is significantly related to the week-ahead volatility for seven currencies. The number of Google internet searches for the keyword "recession" is also significantly related to the week-ahead volatility for five currencies.

Vlastakis and Markellos (2012) study a sample of 30 of the largest stocks traded on the NYSE and NASDAQ which constitute the Dow Jones Industrial Average index. They interpret web search queries as demand for information, and analyze the contemporaneous relation between Google search index and market variables. The study finds that demand for information at the market level is significantly positively related to historical and implied measures of volatility and to trading volume, even after controlling for market return and information supply. Moreover, information demand increases significantly during periods of higher returns. The analysis of the expected variance risk premium empirically confirms the hypothesis that investors demand more information as their level of risk aversion increases.

Joseph et al. (2011) analyze the search for tickers of stocks in S&P500 from the period 2005-2008 and construct a sentiment factor based on Google search queries that is interpreted as a sentiment measure. They found some cross-sectional explanatory ability of the sentiment factor.

Finally, recent work by Mondria et al. (2010) uses measures of aggregate search frequency from AOL (American Online) search engine as direct measures of attention to study home bias and Wu and Mondria (2011) use Google search index to construct a measure of asymmetric attention and focus on asset pricing implications of investor allocation theories.

III. Data and Methodology

A. Firm data

The data set is stocks from the EURO STOXX 50 Index, Europe's leading blue-chip index for the euro zone. The index covers 50 stocks from 12 euro zone countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. Stocks are traded on different exchanges such as the Euronext, Deutsche Borse, Nasdaq, London Stock Exchange Group and Bolsas y Mercados Españoles. This index combines 'blue chips' that share a currency, the euro, but are headquartered in different geographic areas and operate in different sectors.

Contrasting with studies that have focused on small or neglected stocks to study investor attention, our sample of stocks is composed of salient firms, the largest companies in the euro area. Large stocks typically get more attention from financial media and coverage from sell side analysts, such as more frequent recommendations and earnings forecasts. This difference is important because the evidence on price surges due to investor attention has been provided by small firms (see, e.g., Bank et al., 2011; Li et al., 2011). The fact that our sample is composed of large stocks implies that they are widely followed by investors, media and analysts and therefore relevant information such as changes in fundamentals should be rapidly incorporated in prices. Moreover, theoretical work on limited attention postulates that investor attention can vary across firms, and individual investors can allocate more attention to large firms (Peng, 2005). Finally, the results are less likely to be influenced by liquidity issues.

We consider only firms that are part of the index during the sample period, because the inclusion and exclusion of a stock of a certain index is already an event that is associated with media coverage and investor attention (see Chen et al., 2004; Kaul et al., 2000; Shleifer, 1986).

We draw prices (P) and volume (Vol) of the stocks comprising the index from Bloomberg. Prices are weekly and in euros. Let $P_{i,t}$ and $Vol_{i,t}$ be the observed weekly closing price and volume of stock i with $i = 1, ..., n$ and $t = 0, ..., T$. Thus, the weekly changes in price and volume for stock i are defined as: $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$ and $vol_{i,t} = \ln(Vol_{i,t}/Vol_{i,t-1})$.

B. Google search volume

We use the data collected from "Google Insights for Search" to study the relationship between internet search queries about a company and stock market activity. "Google Insights" is a free service available to the public that registers the evolution of the number of searches on a particular word or set of words.[3] Search queries on Google are aggregated over millions of worldwide users of the Google search engine. On "Google Insights", users would get time series data on the number of times a particular keyword search term is entered into the Google search engine. Data from "Google Insights" is available on a daily basis for a 90-day rolling window and on a weekly basis from the beginning of 2004.

The choice on the search term is wide. Does search on "Santander" refer to the bank or to the city in northern Spain? Is a search on "Carrefour" made by a potential investor or just a user in search of the nearest supermarket? The current technology does not allow us to know the precise final intention of searchers. If there is no way to distinguish the "search for knowledge" from "search to decide", three options arise: (1) look for the complete name of the firm ("Banco Santander SA", for example), (2) like Da et al. (2011) use the ticker of the stock ("SAN"), or (3) like Vlastakis and Markellos (2012) consider the name of the company (only "Santander"). Items of search are presented in Table I.

The default GSVI presented on "Google Trends" is a relative metric and is based on the relation between actual searches and average searches over the period.

$$GSVI = \frac{\text{Actual Number of Searches}}{\text{Average Number of Searches}}.$$

A value of GSVI of 1 means that there was neither a rise nor a fall in the web search interest for

[3] A key issue is whether Google is representative of web search queries in the internet. Search engine rankings in the US can be seen at http://www.comscore.com. According to their data, Google has around 2/3 of market share. World market shares can be seen in http://www.netmarketshare.com/. According to this company, Google has a share of around 85%.

that keyword. If GSVI increases (decreases), it is because the actual number of searches increases (decreases) in relation to the average.[4] To control for the overall increase in the number of internet searches over time, the data are normalized. The total number of web searches for a particular keyword is divided by the overall total number of Internet searches during a particular time period.[5]

The sample starts in January 2004 and ends in June 2011 and the frequency is weekly, because Google data are only available after January 2004 and only allow the weekly export of data, although the service is updated daily.[6]

After applying the filters, the final sample is 36 listed companies from seven countries and nine sectors as presented in Table I. As Da et al. (2011), we use the logarithm of GSVI denoted $google_{i,t} = ln(GSVI_{i,t})$, justified by the distributional properties and the simpler interpretation that negative values represent a decrease in the search activity.

To capture abnormal variations in investor attention, we compute the difference between the actual value of the *google* and the average of the last four weeks for each stock in the following way:

$$abn\_google_{i,t} = google_{i,t} - \frac{\sum_{j=1}^{4} google_{i,t-j}}{4}. \tag{1}$$

The variable *abn_google* indicates the extent to which current web searches are different from the average of the 4 last weeks. This measure distinguishes from *google* because it seeks to capture abnormal changes.

To isolate the effects of an increase or decrease in investor attention, we compute the following variables,

[4]Similarly to previous studies, we adopt-up mode "on" for the sake of temporal fairness, where the data are treated as variations from the average, represented by the number 1. In this approach, the value 3 illustrates three times more queries than the average for the whole period considered.

[5]Note that the "Google Insights" system eliminates repeated queries from a single user over a short period of time so that the level of interest in a particular topic is not artificially inflated.

[6]In addition, to increase the accuracy of the findings we exclude stocks with GSVI zero for at least eight consecutive weeks, considering that these observations are unfruitful for research and may even distort the results. The GFD Suez and Munich Re are excluded from the sample after applying this filter.

$$
\begin{aligned}
abn\_google^{+}_{i,t} &= \max(0, abn\_google_{i,t}) \\
abn\_google^{-}_{i,t} &= \min(0, abn\_google_{i,t}),
\end{aligned}
$$

where $abn\_google^{+}_{i,t}$ indicates a rise in investor attention and $abn\_google^{-}_{i,t}$ a decrease in investor attention for firm i at time t.

C. Measuring stock market activity

In this section, we describe measures related with stock market activity such as volume, returns and volatility.

We will analyze the relation of web searches with changes in volume (vol) but also with abnormal volume. We compute abnormal volume (abn_vol) as in Barber and Odean (2008):

$$abn\_vol_{i,t} = \frac{\ln(Vol_{i,t})}{\frac{\sum_{j=1}^{52} \ln(Vol_{i,t-j})}{52}}. \tag{2}$$

We will also analyze whether search queries are related with returns (r) and absolute returns ($abs\_r = |r|$). The latter variable is used by Corwin and Coughenour (2008) as a measure of investor attention.

Abnormal returns for firm i at time t $\alpha_{i,t}$ are, as in Carhart (1997), the difference between the predicted excess returns and the realized excess returns:

$$\alpha_{i,t} = (r_{i,t} - r_{f,t}) - \beta^{*}_{i,t-1} \cdot (r_{M,t} - r_{f,t}) + \epsilon_{i,t}, \tag{3}$$

where $\beta^{*}_{i,t-1}$ for each firm is estimated with a 52-week rolling window, r_M is the return of the EURO STOXX index and r_f is the return of 1 week EURIBOR rate.

To analyze the behavior of volatility, we use the estimated volatility for each firm separately from a GARCH(1,1) model ($\hat{\sigma}_{garch}$) as a proxy for firm price volatility, and it is computed as

$$\begin{aligned} r_{i,t} = & \quad \mu + \sigma_{i,t}\epsilon_{i,t} \\ \sigma_{i,t}^2 = & \quad \alpha_0 + \alpha_1 \varepsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2, \end{aligned} \tag{4}$$

where $\varepsilon_{i,t} = \sigma_{i,t}\epsilon_{i,t}$ is the prediction error for firm i at time t, $\sigma_{i,t} > 0$ is the conditional standard deviation of the underlying stock return (denoted volatility) and $\epsilon_{i,t} \sim NID(0,1)$. We impose the conditions $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$ to guarantee that the conditional variance for each firm is positive and $\alpha_1 + \beta_1 < 1$ to assure its stationarity.

Finally, following Dimpfl and Jank (2011) and Vlastakis and Markellos (2012), we compute the realized volatility measure for firm i at week t, from daily data as

$$\hat{\sigma}_{real,i,t} = \sqrt{\sum_{j=0}^{4} r_{i,j}^2}. \tag{5}$$

Each weekly value is computed based on 5 week days and like Dimpfl and Jank (2011) and Vlastakis and Markellos (2012) we use the logarithm of the computed value. Table II presents the summary statistics of firm variables.

We use r_M to represent the logarithmic variations of the EURO STOXX 50 index and $\hat{\sigma}_{market}$ refers to the implicit volatility of the index.

D. Methodology

To investigate whether web search queries (proxied by *abn_google*) anticipate market activity we estimate the following equation:

$$x_{i,t} = a + b \cdot abn\_google_{i,t-1} + c \cdot Z_{i,t-1} + u_{i,t}, \tag{6}$$

where the dependent variables are the previously defined return measures, volume and volatility (real and GARCH), that is, $x_{i,t} = \{r_{i,t}, \alpha_{i,t}, vol_{i,t}, abn\_vol_{i,t}, \hat{\sigma}_{i,t}\}$ and $Z_{i,t-1}$ are control variables such as previous week return, volume and volatility because these variables have been used as proxies of investor attention (see e.g. Barber and Odean, 2008; Chemmanur and Yan, 2009; Gervais et al., 2001) and finally, firm and time dummies for dealing with the heterogeneity and time effects of the data. If b is statistically different from zero, then web search queries show predictability on the behavior of the market variable.

To ascertain the existence of asymmetric effects, we define a similar equation but that differentiates between negative and positive variations in *abn_google*:

$$x_{i,t} = a + b^{+} \cdot abn\_google^{+}_{i,t-1} + b^{-} \cdot abn\_google^{-}_{i,t-1} + c \cdot Z_{i,t-1} + u_{i,t}. \tag{7}$$

Asymmetry is defined as the rejection of the null hypothesis of equality of the coefficients of $abn\_google^{+}_{i,t-1}$ and $abn\_google^{-}_{i,t-1}$, that is, $H_0 : b^{+} = b^{-}$. Thus, we reject the null H_0 if the variables are statistically different.[7] In this case an increase or decrease in search queries has a different impact in stock market activity.

Given the structure of the data, we estimate equations (6)-(7) using panel data. Some advantages of this approach are that it enhances both quality and quantity of data and allows more accurate model inference to control the impact of omitted variables and to study the dynamics of the variable of interest with a relatively short time series. Moreover, intercepts can differ according to firms for capturing cross-sectional heterogeneity. In addition, since we have dynamic effects, the inclusion of firm dummies diminishes the biases in the estimation and the time dummies capture time effects of the data.

IV. Empirical Results

This section presents the empirical results. We start by showing correlations between web search queries and stock market activity and the results of portfolios of stocks sorted according to frequency of web search queries. Next, we conduct a regression analysis making use of several controls.

[7] If variables are not statistically significant, the null hypothesis will not be tested (see Ramos and Veiga, 2011, 2012).

A. Correlations

Table III presents the correlation coefficients between the indicators of web search queries and market variables calculated for all firms, simultaneously. To analyze if web search queries lead or lag stock market activity, we use abn_google_{t-j}, where $j = -1, 0, 1$. The first column shows contemporaneous correlations. Web search queries are positively correlated with volume (*vol*), absolute returns (*abs_r*) and real volatility ($\hat{\sigma}_{real}$). The second column presents correlation coefficients between the main variables and web search queries of the previous week. Correlation between abn_google_{t-1} and volume, volatility measures and absolute returns is positive and statistically significant, and correlation between abn_google_{t-1} and returns is negative. The third column presents correlations between market variables and search queries of the following week. Abnormal volume, returns and $\hat{\sigma}_{garch}$ are negatively correlated with changes in web search queries in the next week (abn_google_{t+1}). In sum, the stronger evidence is for an increase in web searches queries being followed by an increase in volume and volatility, and a decrease in returns.

B. Portfolios sorted according to web search queries

We next construct portfolios of stocks sorted by changes in web search queries. Every week, stocks are sorted by the level of changes in search queries (*abn_google*) and separated in quartiles. Q1 is the portfolio of stocks with the largest increase in web searches and Q4 is the portfolio of stocks with the largest drop in web search queries. Then, we compute the mean (or the median) of the variable of interest for each of the four portfolios. Week 0 is the week of the formation of the portfolio and we focus on the difference Q1-Q4 from four weeks before portfolio formation until four weeks after portfolio formation, i.e., from week -4 to week +4. Results for the gap Q1-Q4 of the different variables are presented in Figures 2, 3 and 4.

Figure 2 shows the results for volume variables. We see that there is almost no difference between changes in volume and abnormal volume of stocks with high and low web search from week -4 to week -1. In week 0, there is a slight increase in the volume traded; the difference Q1-Q4 in *vol* is 3.25% in week 0 and 7.99% in the week after the portfolio formation. Then, we observe that after week 1 the gap becomes slightly negative (in week 2, 3 and 4), which means that stocks previously with highest search queries see a drop in trading. The same pattern can be observed when we inspect abnormal volume. There is an increase in abnormal volume in week 0 that reaches the peak one week after portfolio formation. Then abnormal volume falls for previously highly searched stocks. Overall, the evidence suggests a surge in volume traded in the week subsequent to an increase in web search queries, which is consistent with the presence of unsophisticated investors. The results are similar if we use the median instead of the mean.

Next, Figure 3 depicts the patterns of return measures around search queries (results are in basis points). The observed patterns are more fuzzy. Absolute returns show a peak for the difference Q1-Q4 at week +1; the mean is 32 b.p., but the median peaks at week 0. The next panel shows raw returns. There are differences for the mean and median returns of the portfolio. The mean peaks in week -2 (the gap is 11 b.p.) while the median peaks in week +1. After week +1, the returns of the portfolio Q1-Q4 drop. This trend is similar for α. There is a slight increase at the beginning, but α decreases one week after portfolio formation. The last panel shows 4-week cumulative returns. There is a visible upward trend until week +1 where the gap Q1-Q4 is 10 b.p., but then the trend reverses and cumulative returns drop. At week +4, four week cumulative returns are -24 b.p.

Figure 4 shows the difference in volatility of the portfolio of highly searched stocks minus the least searched stocks. The figure depicts a rising trend, which starts rising slowly in week -2 and peaks in week +1, and then reverses. Thus, stocks with an increase in search queries tend to register a surge in volatility.

In summary, the portfolio approach suggests that web search queries might be related with stock market activity. The figures highlight noticeable differences in market variables between stocks with higher and lower search queries that are, nevertheless, short-lived.

C. Predictability of web search queries

The results of the previous sections show that stocks with changes in web search queries have more intense market activity in the following week. In this section we test specifically whether *abn_google* leads next week market variables using equations (6) and (7) including several control variables.

Table IV presents the results for the volume measures, Panel A for changes in volume and Panel B for abnormal volume. The results indicate that an increase in web search queries is followed by an increase in volume. Column (1) of the different panels shows that *abn_google* is statistically significant and has positive coefficients for *vol* and *abn_vol*. Next, we test equation (7) to analyze whether predictability of web searches is different for increases and decreases in investor attention. Looking at column (2), we see that an increase in search queries ($abn\_google^{+}_{t-1}$) leads an increase in volume and a decrease in search queries leads a fall in volume, but the effect is stronger for increases in search queries. This is supported statistically by the rejection of the null hypothesis of equality of the coefficients in the last row of the table (asymmetry test).

As the observed pattern can uncover convexity, we try another nonlinear specification by computing the square of the Google variable ($abn\_google^{2}_{t-1}$), and test whether it is statistically significant in the following equation:

$$x_{i,t} = a + b \cdot abn\_google_{i,t-1} + c \cdot abn\_google^{2}_{i,t-1} + d \cdot Z_{i,t-1} + u_{i,t}. \qquad (8)$$

If $abn\_google^{2}_{t-1}$ is statistically significant and the coefficient c is positive, then an increase in web search queries has a proportionally larger impact on variable x than a decrease. Conversely, if $c < 0$ and $abn\_google^{2}_{t-1}$ is statistically significant, then an increase in web search queries has a proportionally smaller impact than a decrease. Column (3) of the different panels shows that volume has a convex relation with web search queries of the previous week, i.e., an increase in web searches has a larger impact than a decrease.

Table VI shows whether changes in search queries predict next week returns. Panels A, B and C show the results for raw returns, absolute returns and abnormal returns, respectively. abn_google_{t-1} is not statistically significant except for absolute returns. Panels D and E analyze whether abn_google_{t-1} is a predictor of 4 and 8-week cumulative returns ($r_{(0,4)}$ and $r_{(0,8)}$), and in this case we find that an increase in web search activity precedes a statistically significant drop in cumulative returns in the next 4 weeks; however, the drop is not statistically significant for 8-week cumulative returns. In untabulated results we find that the relation is not convex for any of the variables.[8]

Table VI presents the results of testing whether web search queries lead next week volatility. Columns (1) show that abn_google_{t-1} is statistically significant with a positive coefficient; thus an increase in search queries precedes an increase in stock volatility for both measures of volatility, $\hat{\sigma}_{real}$ and $\hat{\sigma}_{garch}$. Column (2) shows the results of testing for asymmetric effects. We see that the impact is asymmetric, an abnormal increase in web searches precedes an increase in volatility, while a decrease does not seem to impact volatility, but column (3) shows that the relation is not convex.

The overall evidence supports changes in web search queries being related with one-week ahead stock market activity; in particular, web search queries predict a surge in liquidity and volatility, which is statistically significant after controlling for measures commonly used to proxy investor attention such as abnormal volume, volatility and returns. The results indicate a drop in returns in the following weeks in our sample of salient stocks after an increase in levels of attention, which can be related with the disposition effect. Following this hypothesis, after the rise in investors' attention levels, investors may notice winner stocks in the portfolio and decide to sell them, and the selling pressure makes stock prices fall.

D. Web search queries and price breakthroughs

Attention seems a necessary condition to trade, but investors also need to process information to trigger the investment decision. In this section we analyze the effect of price references such

[8]Results are available from authors upon request.

as the 52-week high and low prices on investor attention. We posit that attention can interact with behavioral biases affecting the way investors react to information.

We focus on the case of the 52-week high and low prices because they are a piece of information that is easily available on financial sites and newspapers, thus with low search costs, and can be easily obtained by unsophisticated investors. Their effects on investment decisions at several levels are well documented and are supported by behavioral theories.[9] For instance, George and Hwang (2004) find that the 52-week high price explains a large portion of the profits from momentum investing, and they argue that investors use this as an anchor when they evaluate new information.[10] Huddart et al. (2009) argue that if investors are able to evaluate only a limited number of companies, stocks entering investors' choice sets will be those that attract their attention. Stocks that break their trading ranges are likely to attract investor attention because the 52-week highs and lows are widely reported. They find increased volume when stocks break through their 52-week high or low, more buys and positive subsequent returns; this is due to the buying pressure, which they attribute to individual investor attention (Barber and Odean, 2008).[11] Barberis and Xiong (2009) emphasize that the 52-week high is a price in which investors are particularly willing to realize gains.[12] Driessen et al. (2011) analyze whether option-implied volatilities change when stock prices approach or break through their 52-week high or low. They find that implied volatilities decrease when approaching a high or low, and that implied volatilities increase after breakthroughs. They argue that the approach results can be explained by anchoring theory, while the breakthrough results are consistent with anchoring and the investor attention theory.

[9] Several works have empirically found that hitting the high or low affects trading behavior (Grinblatt and Keloharju, 2001), exercise of executive stock options (Heath et al., 1999), exercise of exchange-traded stock options (Poteshman and Serbin, 2003) and pricing of mergers and acquisitions (Baker et al., 2012).

[10] Anchoring is a cognitive bias that can be loosely described as the common human tendency to rely too heavily on one piece of information when making decisions (Tversky and Kahneman, 1974).

[11] Limited attention is also related to the concept of bounded rationality. Bounded rationality assumes that decision-makers are only rational within limits. These limits may result from the decision environment or from the computational capacities of the agent. See Gifford (2005) for a discussion of limited attention as a bound on rationality.

[12] Prospect theory is a behavioral economic theory that says that people make decisions based on the potential value of losses and gains rather than the final outcome, and that people evaluate these losses and gains using interesting heuristics (Kahneman and Tversky, 1979).

In this section we hypothesize that if web search queries are related with the attention of unsophisticated investors, then the predictability of investor attention can be exacerbated or mitigated by salient cues such as the 52-week high and low prices, because they are reference points commonly used to make investment decisions.

To analyze this issue we use both 52-week high and low prices of the stock market and of the firm as they can give us insights into the effects of limited attention. Several works have noted individual investors have limited attention and processing capabilities and inattentive investors fail to incorporate firm specific news. Peng (2005) models the effects of a capacity constraint on the amount of information processed. He theorizes that due to capacity constraint, larger stocks attract more capacity allocation to the extent they make a greater contribution to the uncertainty in the investors portfolio. As a result, they tend to have a greater supply of information, their prices incorporate fundamental shocks at a faster pace and exhibit less volatility to exogenous announcements from firms. Peng and Xiong (2006) model shows that limited investor attention leads to category-learning behavior, i.e., investors tend to process more market wide information than firm specific information. According to previous work, it is more likely to find the sign of interaction variables statistically significant for the 52-high and low of the market than for the 52-high and low of firms.

Following Driessen et al. (2011) we create dummy variables. Whenever the price is higher than 52-week high ($P^{high}_{i,t}$) or lower than 52-week low ($P^{low}_{i,t}$). We define the following indicator $P^{high}_{i,t}$=1 if $net\_r^{+}_{i,t} > 0$ and $P^{low}_{i,t} = 1$ if $net\_r^{-}_{i,t} < 0$, where $net\_r^{+}_{i,t} = max(0, ln(P_{i,t}) - ln[max(P_{i,t-1}, ..., P_{i,t-52})])$ and $net\_r^{-}_{i,t} = min(0, ln(P_{i,t}) - ln[min(P_{i,t-1}, ..., P_{i,t-52})])$, where i is the index of firm and t is the index of time. Yuan (2012) interpret this variable as proxy for attention–grabbing events and finds that the dummy variable negatively predicts next-day returns because of the selling pressure the next day. For the price range, we also follow the thresholds of Driessen et al. (2011) and P^{Range_high} is a dummy variable that indicates whenever the price is in a 3% range below the 52-week high and P^{Range_low} is a dummy variable that indicates whenever the price is in a 3% range above the 52-week low. Similarly, M^{high} and M^{low}

are dummy variables that indicate whether stock market indexes break through a 52-week high or low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicate if the market value of the index is in a 3% range below the 52-week high and above the 52-low, respectively.

We re-estimate equations (6) and (8) with the dummy variables interacting with changes in Google search index to see whether they impact the leading effect of web search queries. This approach has the advantage of disentangling the effects of web search queries and the breakthroughs, but also the joint effect of both. If the interaction coefficient is positive (negative) then it enhances (mitigates) web search queries as a predictor.

We separate the analysis in two parts. First, we analyze firm 52-week breakthroughs and secondly, stock market 52-week breakthroughs, and their impact on predictability of volume, volatility and returns. As the analysis focuses on the effects of breakthroughs on web search predictability, tables only present coefficients of the main variables.[13]

Predictability of Volume Table VI exhibits the results for predictability of volume when abn_google_{t-1} interacts with firm 52-week high and low prices (P^{high} and P^{low}, respectively). Panel A.1 shows the results for volume and Panel A.2 for abnormal volume. Column (1) reveals a linear relation, but when firm prices hit a 52-week high the relation becomes convex, the predictability for liquidity is higher. However, the interaction coefficient is only statistically significant for volume. Column (2) shows again a linear relation but when firm price drops below a 52-week low, the relation becomes concave, an increase in web search queries precedes a decrease in volume, but it is not statistically significant. The dummies P^{high} and P^{low} have different signs for volume and abnormal volume and are negative for volume but positive for abnormal volume. Columns (3) and (4) show that when prices are near a 52-week high and low (P^{Range_high} and P^{Range_low}, respectively), the interaction coefficient is positive for 52-week high and negative for 52-week low; this is similar to the results of breakthroughs, but it is not statistically significant.

Panel B shows the results of interacting abn_google_{t-1} with a dummy that indicates when

[13]Complete tables are available from authors upon request.

the stock market hits a 52-week high or low (M^{high} and M^{low}, respectively). Column (1) shows that the interaction variable is positive when the stock market hits a 52-week high; thus, the relation is convex indicating that search queries lead a stronger increase in volume when the stock market hits a 52-high. Column (2) shows that the interaction variable is negative when the stock market hits a 52-week low, suggesting that an abnormal increase in Google queries precedes a decrease in volume. The dummies are positive and statistically significant pinpointing a surge in volume when the stock market hits a breakthrough in line with investor attention explanations. Columns (3) and (4) show that when price levels are in the range of a 52-week high and low, the interaction coefficient is only statistically significant when the market index ranges a 52-week high. The indicators M^{Range_high} and M^{Range_low} display that abnormal volume is higher when price levels are in the range of a 52-week high and low in line with anchoring theory. Thus, the predicability of web search queries, or investor attention, for liquidity is exacerbated when firm prices break through a 52-week high (although the evidence is modest), and breaks through or are in the range of a market 52-week high, and is mitigated when the stock market hits a 52-week low. Market information seems, therefore, more determinant in changing the effects of investor attention.

Predictability of Volatility Table VII shows the results of abn_google_{t-1} as a predictor of volatility, and how it changes when prices hit a 52-week high and low (P^{high} and P^{low}, respectively). Panel A.1 shows the results for $\hat{\sigma}_{real}$ and Panel A.2 for $\hat{\sigma}_{garch}$. The interaction variable for $\hat{\sigma}_{garch}$ is positive and statistically significant when firm prices break through a 52-week low and negative and statistically significant for $\hat{\sigma}_{real}$ when prices hit a 52-week high. However, the stronger evidence is for the statistical significance of the breakthrough dummies. Volatility rises when firm prices reach a 52-week high and low as in results from Driessen et al. (2011). In contrast, when prices are in the range of a 52-week high and low, the interaction coefficients and the dummies are not statistically significant.

Panel B shows the results of abn_google_{t-1} as a predictor of volatility, and how it changes when the market hits or is in the range a 52-week high and low (M^{high} and M^{low}, respectively). Panel B.1 shows the results for $\hat{\sigma}_{real}$ and Panel B.2 for $\hat{\sigma}_{garch}$. The interaction variables are not statistically significant. The dummy variables for breakthroughs indicate an increase in next week's volatility when the stock market hits or is near a 52-week low and a decrease in next week's volatility when market hits or is near a 52-week high, consistent with investor attention and anchoring theories. Overall, the effects of web search queries as a predictor of volatility do not seem to be affect by market breakthroughs, but only when firm prices hit a 52-week high and low.

Predictability of Returns Table VIII shows the results of predictability of return measures when web searches interact with firm 52-week high and low prices (P^{high} and P^{low}, respectively). Panel A shows the results for raw returns. As the interaction coefficient is positive when the firm price hits a 52-week high, the predictive effects are exacerbated. The dummies are not statistically significant as in George and Hwang (2004). The next columns display the results for absolute returns and for cumulative returns. The interaction coefficients are not statistically significant when prices hit breakthroughs. For cumulative returns, the dummy variable is statistically significant when prices hit a 52-week low, indicating a likely rebound in cumulative returns after hitting a 52-week low. Huddart et al. (2009) find an increase in returns and a dominance of buyer-initiated trades when the stock prices reach a 52-week high or low.

Panel B shows the results when abn_google_{t-1} interacts with a 52-week market high and low, (M^{high} and M^{low}, respectively). Panel A shows the results for raw returns. The interaction variable is positive and statistically significant when the market hits or is in the range of 52-week high and is negative and statistically significant when the stock market is in the range of a 52-week low. The dummy variables are negative when the market hits or is in the range of a 52-week low, which may be due to selling pressure; they are positive when the market is in the range of a 52-week high, perhaps due to buying pressure. Results are in line with anchoring and investor attention hypotheses. Panel B shows the results for absolute returns, but we do not find statistical significance for interaction variables. Panel C shows the results for cumulative returns, and the interaction variable is negative and statistically significant when prices break through a 52-week low.

In summary, results confirm our hypothesis that investor attention interacts with behavioral biases. The predicability of web search queries for returns is exacerbated when firm prices break through a 52-week high, and break through or range a market 52-week high and are mitigated when the stock market hits a 52-week low. Market information seems therefore more important in changing the effects of investor attention in line with works that advocate that investors' limited attention leads then to process more market and sector wide information than firm-specific information (Peng and Xiong, 2006). Results also provide support for the investor attention and anchoring theories as market breakthroughs affect volume and prices in line with George and Hwang (2004) and Huddart et al. (2009) results. Finally, and indirectly, we can also read that predictability of web search queries is robust to other attention grabbing events such as the 52-week high and low prices.

E. Web Search Queries for the Stock Market Index

In this subsection we investigate the predictability of web search queries for the stock market index. We study whether there are subsequent changes in the returns of the stock market index, of the stock index futures, and of the implied volatility of the EURO STOXX index after changes in web search queries. An important difference from previous analysis is that individuals do not trade directly on the index (unless they trade stock index futures)[14], so there is not a direct match between the asset searched and the asset traded. We use the Google search volume index for the keyword EURO STOXX, available from 2006 onwards, and test whether it precedes changes in the stock market. We use r_M to represent the logarithmic variations of the EURO STOXX 50 index and $\hat{\sigma}_{market}$ refers to the implicit volatility of the index.

Table IX presents the results, Panel A for stock index returns and Panel B for futures in-

[14] We have used *open interest* to measure volume but the impact of web search queries was not statistically significant.

dex returns. Column (1) shows that *abn_google* is statistically significant and its coefficient is negative, thus an increase in web search queries precedes a fall in market returns. Column (2) tests for asymmetry in the coefficients, an increase in *abn_google* is statistically significant while a decrease is not. We notice that the R^2 increases in this specification. Column (3) confirms that the relation is concave and that the R^2 also increases substantially in this specification. Panel B tests *abn_google* as predictor of the return of the stock index futures and the results are similar, confirming a concave relation.

The next columns show whether stock market breakthroughs impact the predictability of web searches. Columns (4) and (5) show the results of conditioning on stock market 52-week highs and lows. We see that the interaction coefficient is positive for a 52-week market high and negative for a 52-week market low. This implies that the relation is less concave when the stock market index hits a 52-week high and more concave when it hits a 52-week low. However, the interaction variables are not statistically significant.

Table X shows the results of whether *abn_google* precedes changes in the implied volatility of the index. *abn_google* is statistically significant and its coefficient positive; thus an increase in web searches precedes an increase in implied volatility. Column (2) tests for asymmetry effects but the coefficient of increases or decreases in investor attention are quite similar and their equality is not rejected. Columns (3)-(6) test whether the predictive ability of search queries is affected by a 52-week market high and low. The interaction variable is statistically significant and its coefficient is negative; thus the coefficient is smaller when stock market breaks through a 52-week high. For the 52-week low, the interaction variable is not statistically significant. Next we analyze when the stock index ranges a 52-week high and low. When it is close to the bottom, the coefficient is positive and statistically significant; thus an increase in web search is followed by an increase in volatility. Driessen et al. (2011) find that implied volatilities decrease when approaching a 52-week high and low, and increase after a breakthrough. We only find a decrease in implied volatility when the stock market ranges a 52-week high; the other dummies are not statistically significant.

Two closing remarks. First, as implied volatility tends not be driven by liquidity issues, it is hard to attribute predictability of web searches to them. Second, implied volatility comes from trades on the option market where sophisticated investors operate. The finding that web search predicts implied volatility seems to indicate that it contains information not known by market professionals.

V. Robustness

In this section we examine whether results are robust to different specifications. To investigate whether our results are sensitive to our variable definition, we conduct a variety of untabulated specification checks (see the supplementary appendix). In all cases results are robust.

Alternative variable specifications We have checked whether results hold with another specification of web search queries like the measure used by Da et al. (2011):

$$ASVI_{i,t} = ln(GSVI_{i,t}) - ln(median(GSVI_{i,t-1}, ..., GSVI_{i,t-8})).$$

We have reestimated equations and results are kept.

We test another measure of volatility provided by Schwert (1989) ($\hat{\sigma}_{schwert}$) that relies on the absolute value of the residuals obtained by fitting an autoregressive model to firm returns, that is:

$$r_{i,t} = \alpha + \sum_{j=1}^{L} \phi_j r_{i,t-j} + s_{i,t},$$

where $s_{i,t}$ follows a normal distribution with mean zero and variance ψ^2 for each i. ϕ_j is the coefficient of the lagged j oil price change. The model, for each i, is estimated by OLS and the regression lag length (L) is determined by the usual significance tests and the BIC. In our case $L = 1$. The volatility is then the absolute value of the regression residuals, $\hat{s}_{i,t}$.

We tried other specifications for prices exceeding a 52-week high or low, and also used the variation instead of the dummy variables. Results are maintened.

Web search queries and volatility–A GARCH specification To confirm the effect of Google search queries on stock volatility we try other model specifications. We estimate two GARCH models where we include (1) changes in web searches and (2) increases and decreases separately, in the conditional variance equations. These specifications permit the analysis of whether web search changes affect conditional variances and consequently volatility. The GARCH models with exogenous variables in the conditional variances are as follows:

$$r_{i,t} = a + b \cdot r_{i,t-1} + \sigma_{i,t} \cdot \epsilon_{i,t} \tag{9}$$

$$\sigma^2_{i,t} = \alpha_0 + \alpha_1 \cdot \varepsilon^2_{i,t-1} + \alpha_2 \cdot \sigma^2_{i,t-1} + \alpha_3 \cdot abn\_google_{i,t-1}, \tag{10}$$

$$\sigma^2_{i,t} = \alpha_0 + \alpha_1 \cdot \varepsilon^2_{i,t-1} + \alpha_2 \cdot \sigma^2_{i,t-1} + \alpha_3 \cdot abn\_google^{+}_{i,t-1}, \tag{11}$$

$$\sigma^2_{i,t} = \alpha_0 + \alpha_1 \cdot \varepsilon^2_{i,t-1} + \alpha_2 \cdot \sigma^2_{i,t-1} + \alpha_3 \cdot abn\_google^{-}_{i,t-1}, \tag{12}$$

where $i = 1, ..., 36$, the mean equation (9) is the same for the three variance specifications ((10), (11) and (12)) and we fit each model to the observations of each firm i. The conditions on the parameters of model (4) apply here for the positiveness and stationarity of the conditional variances. Once more, $\epsilon_{i,t} \sim NID(0,1)$.

The results confirm that web search queries lead volatility and web search queries have predictive power beyond the GARCH(1,1).

Subperiods To analyze whether the results are consistent in the sample and whether the subprime crisis has impacted the results, we divided the sample into three subperiods: 1) January 2004 until end of July 2007, before the subprime crisis; 2) August 2007 until December 2008, during the crisis; 3) January 2009 until June 2011, after the crisis. Results hold.

Investor Sentiment To control for investor sentiment we use market turnover in the specifications. Baker and Wurgler (2007) find that younger and unprofitable stocks with low capitalization are likely to be disproportionably sensitive to broad waves of investor sentiment. Accordingly, we do not expect results to be affected since our sample are large firms. As expected results are maintained.

VI. Conclusion

Search engines are an easy and powerful source of information that can be used to gather information in a variety of issues. Many research areas are using data from search engines such as Google, Yahoo and AOL in order to get short term forecasts. This data seems to provide better indication of consumers' behavior or decisions than advertising or mention on the news because searching for information on the internet is more likely to be related to an action. A growing number of search queries for a keyword reflects interest and might indicate a future behavior.

Also recent finance research concurs that web searches are a more direct measure of investors' attention than previous measures such as large price movements, or large variations in volume; in particular, studies seem to concur that it captures small investor attention (Bordino et al., 2012; Da et al., 2011).

We analyze whether web search queries are related with market activity in a sample of European stocks of the EURO STOXX index. The results show that web search queries precede changes in volume and volatility. An increase in search queries leads a short-lived surge in volume and volatility, that is rapidly reversed in the following week. The fact that the impact is higher in the following week suggests the presence of less sophisticated investors. Web search for the market index precedes a drop in the returns of the index and of the stock index futures, and an increase in implied volatility; this suggests information is not impounded by market professionals.

The results add to the research in investor attention. We confirm that investor attention precedes trading activity but we do not find pervasive evidence of buying pressure as in Barber and Odean (2008); this may be because our sample is large and salient stocks, i.e., stocks widely followed by investors and analysts, and because our measure of investor attention is also different. Moreover, our results provide empirical support for the limited attention hypothesis as the predictability of investor attention is stronger for market breakthroughs than for firm breakthroughs. We also provide novel evidence that investor attention interacts with salient cues such as 52-week highs and lows, which will enhance (or diminish) the predictive power of search queries. Finally, we also present new evidence regarding on web search queries forecasting volatility both for firms and also for the stock market (given by implied volatility). Although detractors could argue that the result could be driven by liquidity, our sample is composed of large and liquid firms, and the relation between liquidity and volatility tends to be negative. Moreover, implied volatility of the index is not driven by liquidity issues and comes from trading by market professionals.

References

Amihud, Y., Mendelson, H., 2006. Stock and bond liquidity and its effect on prices and financial policies. Financial Markets and Portfolio Management 20 (1), 19–32.

Arbel, A., Carvell, S., Strebel, P., 1983. Giraffes, institutions and neglected firms. Financial Analysts Journal 39 (3), 57–63.

Arbel, A., Strebel, P., 1982. The neglected and small firm effects. Financial Review 17 (4), 201–218.

Askitas, N., Zimmermann, K. F., 2009. Google econometrics and unemployment forecasting. Applied Economics Quarterly 55 (2), 107–120.

Baker, M., Pan, X., Wurgler, J., 2012. The effect of reference point prices on mergers and acquisitions. Journal of Financial Economics 106 (1), 49 – 71.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. The Journal of Economic Perspectives 21 (2), 129–151.

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.

Barber, B., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21 (2), 785–818.

Barberis, N., Xiong, W., 2009. What drives the disposition effect? An analysis of a long-standing preference-based explanation. The Journal of Finance 64 (2), 751–784.

Bodnaruk, A., Ostberg, P., 2009. Does investor recognition predict returns? Journal of Financial Economics 91 (2), 208 – 226.

Bordino, I., Battiston, S., Caldarelli, G., Cristelli, M., Ukkonen, A., Weber, I., 2012. Web search queries can predict stock market volumes. PLoS ONE 7 (7), e40014.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance 52 (1), 57–82.

Carneiro, H. A., Mylonakis, E., 2009. Google trends: A web-based tool for real-time surveillance of disease outbreaks. Clinical Infectious Diseases 49 (10), 1557–1564.

Chemmanur, T., Yan, A., 2009. Product market advertising and new equity issues. Journal of Financial Economics 92 (1), 40–65.

Chen, H., Noronha, G., Singal, V., 2004. The price response to S&P 500 index additions and deletions: Evidence of asymmetry and a new explanation. The Journal of Finance 59 (4), 1901–1930.

Corwin, S. A., Coughenour, J. F., 2008. Limited attention and the allocation of effort in securities trading. The Journal of Finance 63 (6), 3031–3067.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The Journal of Finance 66 (5), 1461–1499.

Desai, R., Lopman, B. A., Shimshoni, Y., Harris, J. P., Patel, M. M., Parashar, U. D., 2012. Use of internet search data to monitor impact of rotavirus vaccination in the United States. Clinical Infectious Diseases 54 (9), 115–118.

Dimpfl, T., Jank, S., 2011. Can internet search queries help to predict stock market volatility? CFR Working Papers 11-15, University of Cologne, Centre for Financial Research (CFR).

Driessen, J., Lin, T.-C., Van Hemert, O., 2011. How the 52-week high and low affect option-implied volatilities and stock return moments. Review of Finance, forthcoming.

Ettredge, M., Gerdes, J., Karuga, G., 2005. Using web based search data to predict macroeconomic statistics. Tech. rep., Communications of the ACM.

Fang, L., Peress, J., 2009. Media coverage and the cross-section of stock returns. The Journal of Finance 64 (5), 2023–2052.

George, T. J., Hwang, C.-Y., 2004. The 52-week high and momentum investing. The Journal of Finance 59 (5), 2145–2176.

Gervais, S., Kaniel, R., Mingelgrin, D., 2001. The high-volume return premium. The Journal of Finance 56 (3), 877–919.

Gifford, S., 2005. Limited attention as the bound on rationality. The B.E. Journal of Theoretical Economics 5 (1).

Gilbert, T., Kogan, S., Lochstoer, L., Ozyildirim, A., 2012. Investor inattention and the market impact of summary statistics. Management Science 58 (2), 336–350.

Ginsberg, J., Mohebbi, M., Patel, R., Brammer, L., Smolinski, M., Brilliant, L., 2009. Detecting influenza epidemics using search engine query data. Nature 457, 1012–1014.

Goel, S., Hofman, J., Lahaie, S., Pennock, D., Watts, D., 2009. What can search predict? Working Paper.

Grinblatt, M., Keloharju, M., 2001. What makes investors trade? The Journal of Finance 56 (2), 589–616.

Grullon, G., Kanatas, G., Weston, J., 2004. Advertising, breadth of ownership, and liquidity. Review of Financial Studies 17 (2), 439–461.

Heath, C., Huddart, S., Lang, M., 1999. Psychological factors and stock option exercise. Quarterly Journal of Economics, 601–627.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2009. Driven to distraction: Extraneous events and underreaction to earnings news. The Journal of Finance 64 (5), 2289–2325.

Huddart, S., Lang, M., Yetman, M. H., Jan. 2009. Volume and price patterns around a stock's 52-week highs and lows: Theory and evidence. Management Science 55 (1), 16–31.

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 (4), 1116–1127.

Kahneman, D., Tversky, A., 1979. Prospect theory: An analysis of decision under risk. Econometrica 47 (2), 263–291.

Kaul, A., Mehrotra, V., Morck, R., 2000. Demand curves for stocks do slope down: New evidence from an index weights adjustment. The Journal of Finance 55 (2).

Kim, A., Meschke, F., 2011. CEO interviews on CNBC. SSRN Working paper.

Li, X., Mahani, R. S., Vallapuzha, Sandhya, 2011. Does investor attention affect stock prices? SSRN Working paper.

Louis, H., Sun, A., 2010. Investor inattention and the market reaction to merger announcements. Management Science 56 (10), 1781–1793.

Merton, R. C., 1987. A simple model of capital market equilibrium with incomplete information. The Journal of Finance 42 (3), 483–510.

Mondria, J., Wu, T., Zhang, Y., 2010. The determinants of international investment and attention allocation: Using internet search query data. Journal of International Economics 82 (1), 85–95.

Peng, D., Rao, Y., Wang, M., 2012. Are top-tens better? a study on investor attention and ranking lists. SSRN Working Paper.

Peng, L., 2005. Learning with information capacity constraints. Journal of Financial and Quantitative Analysis 40 (02), 307–329.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80 (3), 563–602.

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 (11), 1443–1448.

Poteshman, A. M., Serbin, V., 2003. Clearly irrational financial market behavior: Evidence from the early exercise of exchange traded stock options. The Journal of Finance 58 (1), 37–70.

Ramos, S., Veiga, H., 2011. Risk factors in oil and gas industry returns: International evidence. Energy Economics 33, 525–542.

Ramos, S., Veiga, H., 2012. Oil price asymmetric effects: Answering the puzzle in international stock markets. Working Paper.

Richardson, S. A., Sloan, R. G., You, H., 2012. What makes stock prices move? Fundamentals vs. investor recognition. Financial Analyst Journal 68 (2), 1443–1448.

Schmidt, D., 2013. Investors' attention and stock covariation evidence from Google sport searches. Working Paper, INSEAD.

Schwert, G., 1989. Why does stock market volatility change over time? The Journal of Finance 44, 1115–1153.

Seasholes, M. S., Wu, G., 2007. Predictable behavior, profits, and attention. Journal of Empirical Finance 14 (5), 590–610.

Shleifer, A., 1986. Do demand curves for stocks slope down? The Journal of Finance 41 (3), 579–90.

Smith, G. P., 2012. Google internet search activity and volatility prediction in the market for foreign currency. Finance Research Letters 9 (2), 103–110.

Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: Heuristics and biases. Science 185, 1124–1130.

Varian, H. R., Choi, H., 2009. Predicting the present with Google trends. Google Research.

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

Wu, T., Mondria, J., 2011. Asymmetric attention and stock returns. Working paper, Society for Economic Dynamics 2011 Meeting Papers.

Yuan, Y., 2012. Market-wide attention, trading, and stock returns. SSRN Working Paper.

Tables and Figures

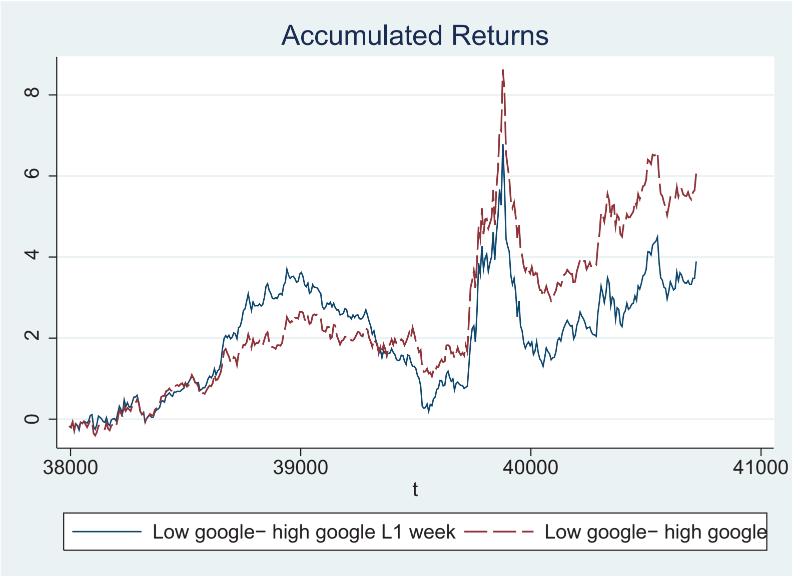

Figure 1. Cumulative returns of a portfolio sorted according to GSVI. Every week stocks are sorted into quartiles. The portfolio is long on stocks with low GSVI and short on high GSVI. The table presents cumulative returns of two strategies: one based on previous week sorting (L1 week) and the other based on contemporaneous sorting.

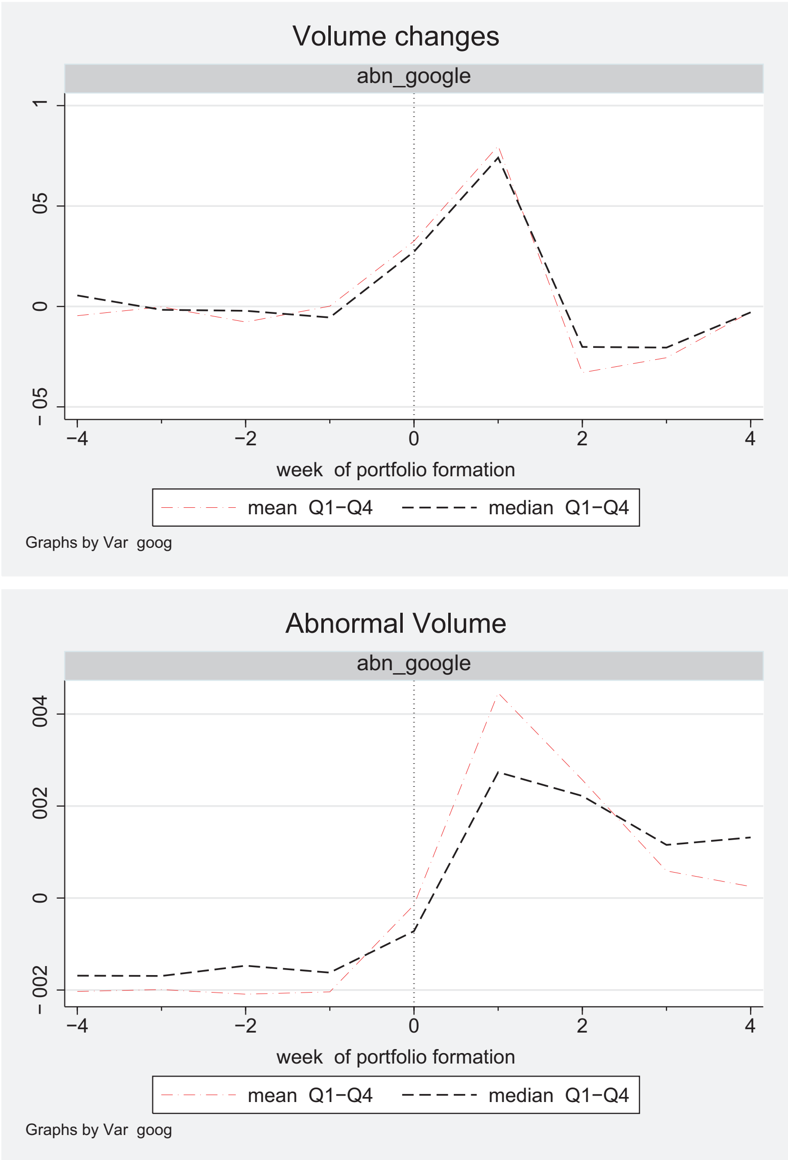

Figure 2. Portfolios formed on web search queries and changes in volume and abnormal volume.

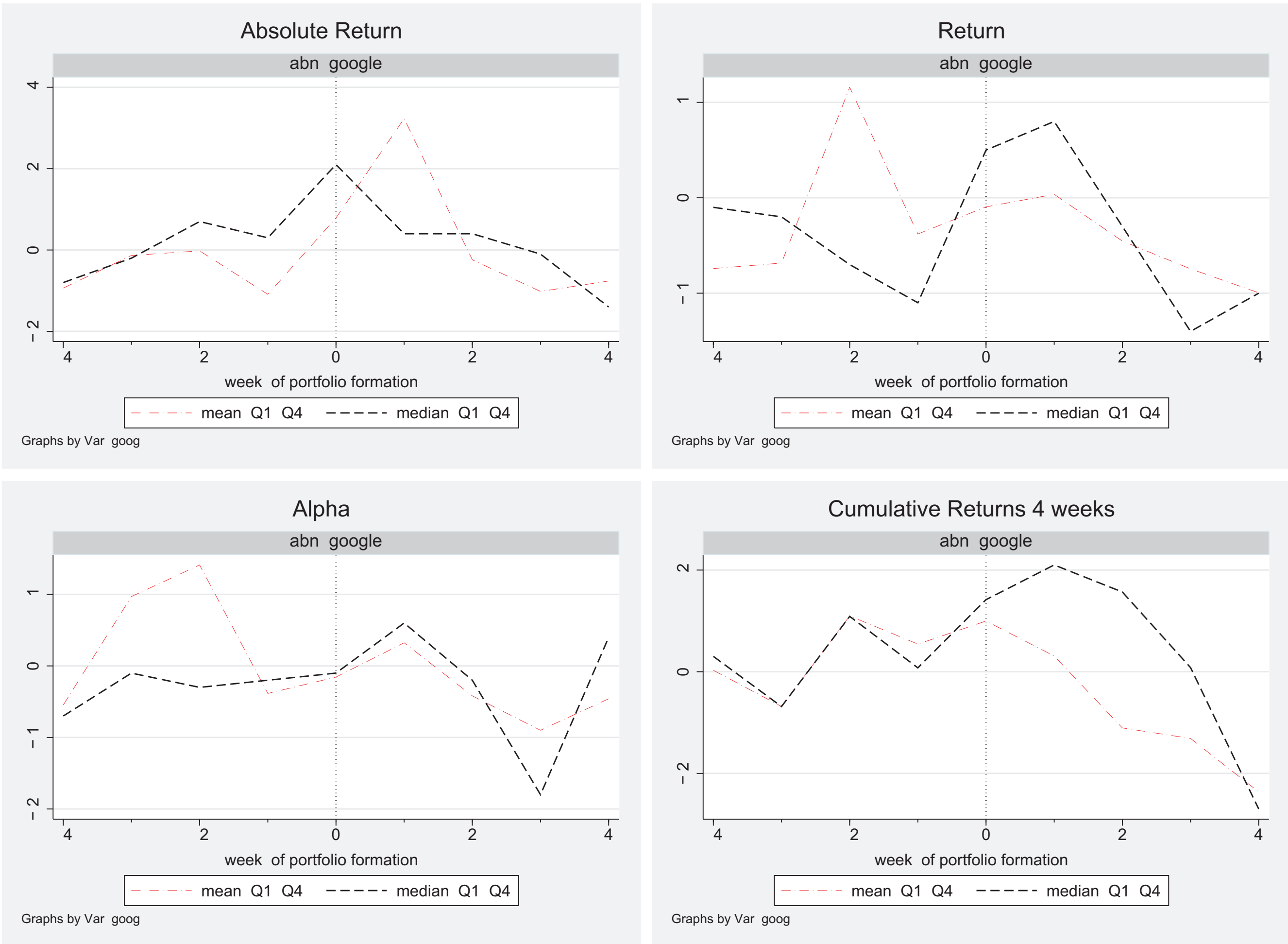

Figure 3. Portfolios formed on web search queries and returns.

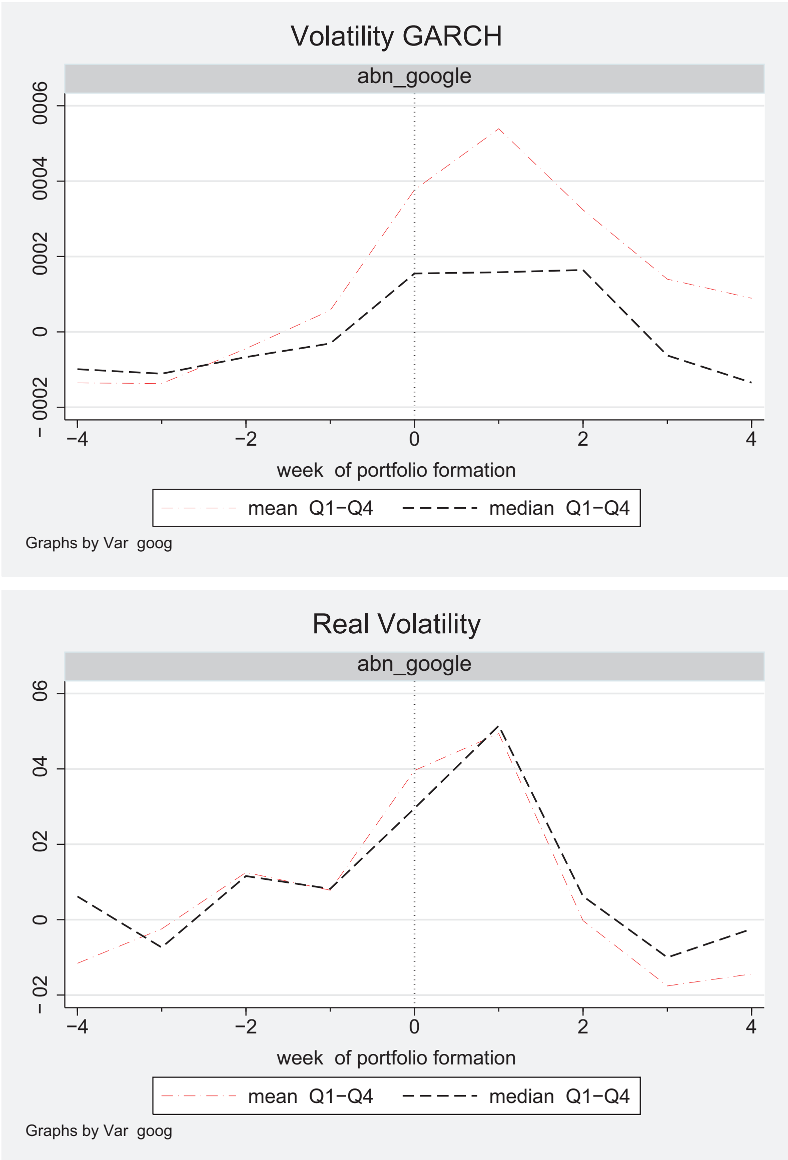

Figure 4. Portfolios formed on web search queries and volatility measures ($\hat{\sigma}_{real}$ and $\hat{\sigma}_{garch}$).

Table I
Sample description

This table presents the sample firms on the EURO STOXX 50 index between 2004-2011. The last column is the item searched on Google engine.

Firm	Country	Industry	Item searched
AIR LIQUIDE SA	France	Basic Materials	"Air Liquide"
ALLIANZ SE-REG	Germany	Financial	"Allianz"
AXA SA	France	Financial	"AXA"
BANCO SANTANDER SA	Spain	Financial	"Santander"
BASF SE	Germany	Basic Materials	"Basf"
BAYER AG-REG	Germany	Basic Materials	"Bayer"
BANCO BILBAO VIZCAYA ARGENTA	Spain	Financial	"BBVA"
BNP PARIBAS	France	Financial	"BNP Paribas"
CARREFOUR SA	France	Consumer, Non-cyclical	"Carrefour"
DAIMLER AG-REGISTERED SHARES	Germany	Consumer, Cyclical	"Daimler"
DANONE	France	Consumer, Non-cyclical	"Danone"
DEUTSCHE BANK AG-REGISTERED	Germany	Financial	"Deutsche Bank"
DEUTSCHE TELEKOM AG-REG	Germany	Communications	"Deutsche Telekom"
E.ON AG	Germany	Utilities	"EON"
ENEL SPA	Italy	Utilities	"Enel"
ENI SPA	Italy	Energy	"ENI"
FRANCE TELECOM SA	France	Communications	"France Telecom"
ASSICURAZIONI GENERALI	Italy	Financial	"Generali"
IBERDROLA SA	Spain	Utilities	"Iberdrola"
ING GROEP NV-CVA	Netherlands	Financial	"ING"
KONINKLIJKE PHILIPS ELECTRON	Netherlands	Industrial	"Philips"
L'OREAL	France	Consumer, Non-cyclical	"LOreal"
LVMH MOET HENNESSY LOUIS VUI	France	Diversified	"LVMH"
MUENCHENER RUECKVER AG-REG	Germany	Financial	"RWE"
REPSOL YPF SA	Spain	Energy	"Repsol"
NOKIA OYJ	Finland	Communications	"Nokia"
COMPAGNIE DE SAINT-GOBAIN	France	Industrial	"Saint-Gobain"
SANOFI	France	Consumer, Non-cyclical	"Sanofi"
SIEMENS AG-REG	Germany	Industrial	"Siemens"
SOCIETE GENERALE	France	Financial	"Societe Generale"
TELECOM ITALIA SPA	Italy	Communications	"Telecom Italia"
TELEFONICA SA	Spain	Communications	"Telefonica"
TOTAL SA	France	Energy	"Total"
UNICREDIT SPA	Italy	Financial	"Unicredit"
UNILEVER NV-CVA	Netherlands	Consumer, Non-cyclical	"Unilever"
VIVENDI	France	Communications	"Vivendi"

Table II
Descriptive statistics on panel regression variables

This table presents the number of observations, mean, standard deviation, 25th percentile, median and the 75th percentile of the variables used in the panel regressions. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR.

Stats	*abn_google*	*vol*	*abn_vol*	*r*	*abs_r*	α	$\hat{\sigma}_{real}$	$\hat{\sigma}_{garch}$
Number of observations	13930	14040	12240	14040	14040	12168	14040	14076
Mean	-0.001	0.003	1.000	-0.000	0.029	-0.000	1.050	0.017
Standard deviation	0.137	0.403	0.0238	0.044	0.033	0.031	0.599	0.010
25th percentile	-0.055	-0.226	0.9873	-0.020	0.010	-0.015	0.662	0.012
Median	-0.003	-0.008	0.999	0.002	0.021	-0.000	1.018	0.014
75th percentile	0.048	0.215	1.013	0.022	0.038	0.014	1.403	0.018

Table III
Correlations

This table presents contemporaneous, lagged and lead correlations between variables. *, ** and *** represent significance at the 10%, 5% and 1% level, respectively. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR.

	Correlations					
	abn_google_t		abn_google_{t-1}		abn_google_{t+1}	
	(1)		(2)		(3)	
vol_t	0.088	***	0.191	***	0.011	
abn_vol_t	0.007		0.202	***	-0.085	***
r_t	-0.007		-0.023	***	-0.017	**
abs_r_t	0.024	***	0.067	***	-0.005	
α_t	0.001		0.003		0.008	
$\hat{\sigma}_{real,t}$	0.028	***	0.056	***	-0.010	
$\hat{\sigma}_{garch,t}$	0.001		0.025	***	-0.021	***

Table IV
Web Search queries (abn_google_t) and predictability of volume

This table presents the estimation of equations (6), (7) and (8). The dependent variables are volume (vol) and abnormal volume (abn_vol) of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (abn_google) as defined in equation (1), positive changes in abn_google (abn_google^+), negative changes in abn_google (abn_google^+), square of changes in abn_google (abn_google^2), changes in volume (vol), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and abnormal volume (abn_vol). The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. p-values are in brackets under coefficients. Standard errors are clustered by firms. All independent variables are lagged 1 week.

Dependent Variable		Panel A: vol			Panel B: abn_vol	
	(1)	(2)	(3)	(1)	(2)	(3)
abn_google_{t-1}	0.283		0.272	0.014		0.014
	(0.000)		(0.000)	(0.000)		(0.000)
$abn\_google^+_{t-1}$		0.350			0.019	
		(0.000)			(0.000)	
$abn\_google^-_{t-1}$		0.202			0.010	
		(0.000)			(0.003)	
$abn\_google^2_{t-1}$			0.080			0.004
			(0.056)			(0.060)
r_{t-1}	-0.419	-0.420	-0.420	-0.023	-0.023	-0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{\sigma}_{garch,t-1}$	-2.787	-2.896	-2.825	0.065	0.045	0.064
	(0.000)	(0.000)	(0.000)	(0.078)	(0.206)	(0.085)
vol_{t-1}	-0.308	-0.306	-0.307			
	(0.000)	(0.000)	(0.000)			
abn_vol_{t-1}				0.513	0.560	0.513
				(0.000)	(0.000)	(0.000)
Constant	-0.045	0.401	-0.047	0.433	0.383	0.432
	(0.548)	(0.000)	(0.533)	(0.000)	(0.000)	(0.000)
Observations	13894	14004	13894	12204	12204	12204
Firms	36	36	36	36	36	36
R^2	0.552	0.55	0.552	0.656	0.659	0.656
Firm Dummies	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes
Asymmetry test		6.3**			8.33***	

Table V: Web Search queries (abn_google_t) and predictability of returns

This table presents the estimation of equations (6) and (7). The dependent variables are: returns (r), absolute returns (abs_r), abnormal returns (α), 4-week cumulative returns ($r_{(0,4)}$) and 8-week cumulative returns ($r_{(0,8)}$) of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (abn_google) defined as in equation (1), positive changes in abn_google (abn_google^{+}), negative changes in abn_google (abn_google^{+}), changes in volume (vol), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and absolute returns (abs_r). The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. p-values are in brackets under coefficients. Standard errors are clustered by firm. All independent variables are lagged 1 week.

	Panel A: r		Panel B: abs_r		Panel C: α		Panel D: $r_{(0,4)}$		Panel E: $r_{(0,8)}$	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
abn_google_{t-1}	0.001		0.008		0.003		-0.011		-0.003	
	(0.709)		(0.000)		(0.346)		(0.013)		(0.538)	
$abn\_google^{+}_{t-1}$		-0.002		0.012		0.003		-0.024		-0.015
		(0.560)		(0.000)		(0.595)		(0.012)		(0.234)
$abn\_google^{-}_{t-1}$		0.005		0.004		0.002		0.004		0.010
		(0.249)		(0.225)		(0.605)		(0.600)		(0.502)
vol_{t-1}	0.001	0.001	-0.001	-0.001	0.001	0.001	-0.002	-0.002	-0.005	-0.005
	(0.485)	(0.460)	(0.197)	(0.224)	(0.159)	(0.163)	(0.329)	(0.295)	(0.011)	(0.010)
r_{t-1}	-0.056	-0.056			-0.057	-0.057	0.010	0.010	0.868	0.868
	(0.001)	(0.001)			(0.000)	(0.000)	(0.635)	(0.632)	(0.000)	(0.000)
$\hat{\sigma}_{garch,t-1}$	0.020	0.024	1.447	1.443	-0.003	-0.003	0.573	0.590	-0.327	-0.312
	(0.698)	(0.637)	(0.000)	(0.000)	(0.959)	(0.959)	(0.002)	(0.001)	(0.431)	(0.447)
abs_r_{t-1}			-0.009	-0.010						
			(0.618)	(0.589)						
Constant	-0.002	0.021	0.001	0.000	0.001	0.001	0.026	0.027	0.069	0.070
	(0.703)	(0.000)	(0.854)	(0.945)	(0.830)	(0.829)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	13894	14004	13894	14004	12168	12168	13750	13750	13750	13750
Firms	36	36	36	36	36	36	36	36	36	36
R^2	0.522	0.522	0.513	0.512	0.026	0.026	0.508	0.508	0.551	0.551
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Asymmetry test		1.21		3.74*		0		3.65**		1.02

Table VI
Web Search queries (abn_google_t) and predictability of volatility

This table presents the estimation of equations (6), (7) and (8). The dependent variables are volatility measures $\hat{\sigma}_{real}$ and $\hat{\sigma}_{garch}$ of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (abn_google) as defined in (1), positive changes in abn_google (abn_google^{+}), negative changes in abn_google (abn_google^{+}), square changes in Google search index (abn_google^{2}), changes in volume (vol), returns (r) and volatility of returns ($\hat{\sigma}_{real}$, $\hat{\sigma}_{garch}$). The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. p-values are in brackets under coefficients. Standard errors are clustered by firm. All independent variables are lagged 1 week.

		$\hat{\sigma}_{real}$			$\hat{\sigma}_{garch}$	
	(1)	(2)	(3)	(1)	(2)	(3)
abn_google_{t-1}	0.119		0.111	0.001		0.001
	(0.006)		(0.011)	(0.004)		(0.007)
$abn\_google^{+}_{t-1}$		0.294			0.002	
		(0.000)			(0.001)	
$abn\_google^{-}_{t-1}$		-0.092			0.000	
		(0.208)			(0.811)	
$abn\_google^{2}_{t-1}$			0.056			0.000
			(0.289)			(0.139)
vol_{t-1}	-0.034	-0.033	-0.034	0.000	0.000	0.000
	(0.026)	(0.035)	(0.027)	(0.189)	(0.190)	(0.190)
r_{t-1}	-0.350	-0.358	-0.350	-0.011	-0.011	-0.011
	(0.003)	(0.002)	(0.003)	(0.013)	(0.012)	(0.013)
$\hat{\sigma}_{real,t-1}$	0.229	0.227	0.229			
	(0.000)	(0.000)	(0.000)			
$\hat{\sigma}_{garch,t-1}$				0.829	0.828	0.829
				(0.000)	(0.000)	(0.000)
Constant	0.685	0.718	0.683	0.002	0.001	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)	(0.000)
Observations	13894	14004	13894	13894	14004	13894
Firms	36	36	36	36	36	36
R^2	0.54	0.539	0.54	0.895	0.895	0.895
Firm Dummies	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes
Asymmetry test		14.98***			11.63***	

Table VI: Changes on predictability of web search queries on volume due to 52–week high and low. Panel A: Firm prices

This table presents the estimation of equations (6) and (8). The dependent variables are volume (*vol*) and abnormal volume (*abn_vol*) of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (*abn_google*) as defined in (1) and square of changes in *abn_google* (abn_google^2). P^{high} and P^{low} are dummy variables that indicate if the price of the stock breaks through a 52-week high or a 52-week low, respectively. P^{Range_high} and P^{Range_low} are dummy variables that indicates if the price of the stock is in the 3% range of 52-week high or a 52-week low, respectively. We also include in the same regression the same control variables as in Table V. The coefficients of some variables are omitted for reasons of space. All independent variables are lagged 1 week. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. p-values in brackets under coefficients. Errors are clustered by firm.

	Panel A.1: *vol*				Panel A.2: *abn_vol*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	0.292	0.274	0.287	0.274	0.014	0.014	0.014	0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$abn\_google^2_{t-1}$	0.012	0.063	0.003	0.061	0.004	0.002	0.002	0.004
	(0.770)	(0.139)	(0.963)	(0.149)	(0.055)	(0.342)	(0.645)	(0.060)
$abn\_google^2_{t-1} \cdot P^{high}_{t-1}$	0.151					0.004		
	(0.004)					(0.161)		
$abn\_google^2_{t-1} \cdot P^{low}_{t-1}$		-0.245			-0.014			
		(0.417)			(0.518)			
P^{high}_{t-1}	-0.016					0.000		
	(0.085)					(0.548)		
P^{low}_{t-1}		-0.021			0.001			
		(0.038)			(0.041)			
$abn\_google^2_{t-1} \cdot P^{Range\_high}_{t-1}$			0.134				0.005	
			(0.135)				(0.409)	
$abn\_google^2_{t-1} \cdot P^{Range\_low}_{t-1}$				-0.054				-0.003
				(0.758)				(0.783)
$P^{Range\_high}_{t-1}$			0.009				0.000	
			(0.185)				(0.979)	
$P^{Range\_low}_{t-1}$				0.001				0.002
				(0.918)				(0.003)
Observations	12204	12204	12240	12240	12204	12204	12204	12204
Firms	36	36	36	36	36	36	36	36
R^2	0.574	0.574	0.576	0.576	0.657	0.656	0.657	0.657
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table VI: (cont.) Panel B: Market prices

This table presents the estimation of equations (6). The dependent variables are volume *vol* and abnormal volume *abn_vol* of stocks of the EURO STOXX index. Independent variables are changes in Google search index (*abn_google*) and square changes in Google search index (abn_google^2). *abn_google* is defined in (1). M^{high} and M^{low} are dummy variables that indicate if the stock index breaks through a 52-week high or a 52-week low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicates if the price of the stock index is in the 3% range of a 52-week high or a 52-week low, respectively. We also include in the same regression the same control variables as in Table V The coefficients of some variables are omitted for reasons of space. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients. Standard errors are clustered by firm.

	Panel B.1: *vol*				Panel B.2: *abn_vol*			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	0.291	0.275	0.277	0.273	0.015	0.014	0.014	0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$abn\_google^2_{t-1}$	0.003	0.063	0.024	0.060	0.001	0.004	0.002	0.004
	(0.946)	(0.148)	(0.599)	(0.158)	(0.700)	(0.055)	(0.452)	(0.060)
$abn\_google^2_{t-1} \cdot M^{high}_{t-1}$	0.182				0.009			
	(0.007)				(0.044)			
$abn\_google^2_{t-1} \cdot M^{low}_{t-1}$		-0.238				-0.033		
		(0.404)				(0.060)		
M^{high}_{t-1}	0.493				0.029			
	(0.000)				(0.000)			
M^{low}_{t-1}		0.942				0.086		
		(0.000)				(0.000)		
$abn\_google^2_{t-1} \cdot M^{Range\_high}_{t-1}$			0.167				0.010	
			(0.038)				(0.082)	
$abn\_google^2_{t-1} \cdot M^{Range\_low}_{t-1}$				0.093				-0.006
				(0.815)				(0.837)
$M^{Range\_high}_{t-1}$			-0.249				0.058	
			(0.004)				(0.000)	
$M^{Range\_low}_{t-1}$				0.071				0.089
				(0.190)				(0.000)
Observations	12204	12204	12240	12240	12204	12204	12204	12204
Firms	36	36	36	36	36	36	36	36
R^2	0.574	0.574	0.576	0.576	0.657	0.657	0.657	0.656
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table VII: Changes on predictability of web search queries on volatility due to 52–week high and low. Panel A: Firm prices

This table presents the estimation of equations (6). The dependent variables are $\hat{\sigma}_{real}$ and $\hat{\sigma}_{garch}$ of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (*abn_google*), *abn_google* is defined in (1), changes in volume (*vol*), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and abnormal volume (*abn_vol*). P_t^{high} and P_t^{low} are dummy variables that indicate if the price of the stock breaks through a 52-week high or a 52-week low, respectively. P^{Range_high} and P^{Range_low} are dummy variables that indicates if the price of the stock is in the 3% range of a 52-week high or a 52-week low, respectively. We also include in the same regression the same control variables as in Table VII. The coefficients of some variables are omitted for reasons of space. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients. Standard errors are clustered by firm.

	Panel A.1: $\hat{\sigma}_{real}$				Panel A.2: $\hat{\sigma}_{garch}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	0.146	0.118	0.118	0.112	0.001	0.001	0.001	0.001
	(0.003)	(0.009)	(0.013)	(0.017)	(0.008)	(0.035)	(0.007)	(0.048)
$abn\_google_{t-1} \cdot P_{t-1}^{high}$	-0.139				0.000			
	(0.042)				(0.695)			
$abn\_google_{t-1} \cdot P_{t-1}^{low}$		0.122				0.004		
		(0.366)				(0.038)		
P_{t-1}^{high}	0.031				0.000			
	(0.120)				(0.028)			
P_{t-1}^{low}		0.042				0.001		
		(0.021)				(0.006)		
$abn\_google_{t-1} \cdot P_{t-1}^{Range\_high}$			-0.007				0.000	
			(0.933)				(0.900)	
$abn\_google_{t-1} \cdot P_{t-1}^{Range\_low}$				0.054				0.001
				(0.718)				(0.364)
$P_{t-1}^{Range\_high}$			-0.009				0.000	
			(0.475)				(0.206)	
$P_{t-1}^{Range\_low}$				-0.010				0.000
				(0.522)				(0.058)
Observations	12204	12204	12240	12240	12204	12204	12240	12240
Firms	36	36	36	36	36	36	36	36
R^2	0.545	0.544	0.546	0.546	0.893	0.893	0.893	0.893
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table VII: (cont.) Panel B: Market prices

This table presents the estimation of equations (6) and (8). The dependent variables are $\hat{\sigma}_{real}$ and $\hat{\sigma}_{garch}$ of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (*abn_google*), *abn_google* is defined in equation (1), changes in volume (*vol*), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and abnormal volume (*abn_vol*). M^{high} and M^{low} are dummy variables that indicate if the stock index breaks through a 52-week high or a 52-week low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicates if the price of the stock index is in the 3% range of a 52-week high or a 52-week low, respectively. We also include in the same regression the same control variables as in Table VII. The coefficients of some variables are omitted for reasons of space. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients. Standard errors are clustered by firm.

	Panel B.1: $\hat{\sigma}_{real}$				Panel B.2: $\hat{\sigma}_{garch}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	0.001	0.001	0.001	0.001	0.128	0.119	0.135	0.114
	(0.026)	(0.019)	(0.040)	(0.025)	(0.004)	(0.012)	(0.010)	(0.016)
$abn\_google_{t-1} \cdot M_{t-1}^{high}$	0.000				-0.025			
	(0.844)				(0.780)			
$abn\_google_{t-1} \cdot M_{t-1}^{low}$		-0.001				0.086		
		(0.679)				(0.638)		
M_{t-1}^{high}	-0.002				-1.070			
	(0.000)				(0.000)			
M_{t-1}^{low}		0.012				1.991		
		(0.000)				(0.000)		
$abn\_google_{t-1} \cdot M_{t-1}^{Range\_high}$			0.000				-0.045	
			(0.566)				(0.555)	
$abn\_google_{t-1} \cdot M_{t-1}^{Range\_low}$				0.001				0.035
				(0.589)				(0.825)
$M_{t-1}^{Range\_high}$			-0.001				0.280	
			(0.026)				(0.002)	
$M_{t-1}^{Range\_low}$				0.009				1.302
				(0.000)				(0.000)
Observations	12204	12204	12240	12240	12204	12204	12240	12240
firms	36	36	36	36	36	36	36	36
R^2	0.893	0.893	0.893	0.893	0.544	0.544	0.546	0.546
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes

Table VIII: Changes on predictability of web search queries on returns due to a 52–week high and low. Panel A: Firm prices

This table presents the estimation of equations (6) and (8). The dependent variables are returns (r), absolute returns (abs_r), abnormal returns (α), 4-week cumulative returns $r_{(0,4)}$ and 8-week cumulative returns $r_{(0,8)}$ of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (abn_google), abn_google is defined in equation (1), changes in volume (vol), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and abnormal volume (abn_vol). M^{high} and M^{low} are dummy variables that indicate if the stock index breaks through a 52-week high or a 52-week low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicates if the price of the stock index is in the 3% range of a 52-week high or a 52-week low, respectively. We also include in the same regression the same control variables as in Table VI. The coefficients of some variables are omitted for reasons of space. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients. Standard errors are clustered by firm.

	Panel A: r				Panel B: abs_r				Panel C: $r_{(0,4)}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	0.000	0.001	0.000	0.002	0.010	0.008	0.010	0.008	-0.015	-0.012	-0.014	-0.015
	(0.992)	(0.647)	(0.995)	(0.488)	(0.000)	(0.001)	(0.001)	(0.002)	(0.012)	(0.047)	(0.030)	(0.007)
$abn\_google_{t-1} \cdot P^{high}_{t-1}$	0.009				-0.006				0.006			
	(0.062)				(0.146)				(0.556)			
$abn\_google_{t-1} \cdot P^{low}_{t-1}$		0.009				0.021				-0.042		
		(0.523)				(0.111)				(0.310)		
P^{high}_{t-1}	0.001				-0.001				-0.003			
	(0.284)				(0.029)				(0.220)			
P^{low}_{t-1}		0.002				0.002				0.009		
		(0.300)				(0.240)				(0.060)		
$abn\_google_{t-1} \cdot P^{Range\_high}_{t-1}$			0.005				-0.002				0.001	
			(0.241)				(0.527)				(0.940)	
$abn\_google_{t-1} \cdot P^{Range\_low}_{t-1}$				-0.005				0.018				0.021
				(0.570)				(0.094)				(0.396)
$P^{Range\_high}_{t-1}$			0.001				0.000				0.000	
			(0.180)				(0.557)				(0.956)	
$P^{Range\_low}_{t-1}$				-0.001				0.003				-0.001
				(0.476)				(0.049)				(0.816)
Observations	12204	12204	12240	12240	12204	12204	12240	12240	12060	12060	12096	12096
Firms	36	36	36	36	36	36	36	36	36	36	36	36
R^2	0.525	0.525	0.525	0.525	0.514	0.515	0.514	0.515	0.512	0.513	0.512	0.512
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table VIII: (cont.) Panel B: Market Prices

This table presents the estimation of equations (6) and (8). The dependent variables are returns (r), absolute returns (abs_r), abnormal returns (α), 4-week cumulative returns $r_{(0,4)}$ and 8-week cumulative returns $r_{(0,8)}$ of stocks of the EURO STOXX market index. Independent variables are changes in Google search index (abn_google), abn_google is defined in equation (1), changes in volume (vol), returns (r), volatility of returns ($\hat{\sigma}_{garch}$) and abnormal volume (abn_vol). M^{high} and M^{low} are dummy variables that indicate whether stock market indexes break through a 52-week high or low. M^{Range_high} and M^{Range_low} are dummy variables that indicate if the market value of the index is in a 3% range below the 52-week high and above the 52-low, respectively VI. The coefficients of some variables are omitted for reasons of space. The sample period runs from 2004:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients. Standard errors are clustered by firm.

	Panel A: r				Panel B: abs_r				Panel C: $r_{(0,4)}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
abn_google_{t-1}	-0.002	0.002	-0.004	0.003	0.010	0.008	0.009	0.008	-0.013	-0.009	-0.015	-0.006
	(0.621)	(0.347)	(0.343)	(0.204)	(0.000)	(0.001)	(0.007)	(0.001)	(0.054)	(0.083)	(0.062)	(0.265)
$abn\_google_{t-1} \cdot M^{high}_{t-1}$	0.014				-0.003				-0.005			
	(0.001)				(0.442)				(0.575)			
$abn\_google_{t-1} \cdot M^{low}_{t-1}$		-0.018				0.029				-0.095		
		(0.476)				(0.184)				(0.077)		
M^{high}_{t-1}	0.003				-0.005				0.154			
	(0.636)				(0.088)				(0.000)			
M^{low}_{t-1}		-0.019				0.000				-0.232		
		(0.044)				(0.963)				(0.000)		
$abn\_google_{t-1} \cdot M^{Range\_high}_{t-1}$			0.012				0.000				0.003	
			(0.016)				(0.988)				(0.783)	
$abn\_google_{t-1} \cdot M^{Range\_low}_{t-1}$				-0.031				0.020				-0.138
				(0.147)				(0.222)				(0.019)
$M^{Range\_high}_{t-1}$			0.018				0.012				-0.033	
			(0.000)				(0.000)				(0.002)	
$M^{Range\_low}_{t-1}$				-0.044				-0.001				-0.227
				(0.000)				(0.831)				(0.000)
Observations	12204	12204	12240	12240	12204	12204	12240	12240	12060	12060	12096	12096
Firms	36	36	36	36	36	36	36	36	36	36	36	36
R^2	0.525	0.525	0.526	0.526	0.514	0.515	0.514	0.515	0.512	0.513	0.512	0.514
Firm Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Table IX: Web search queries and predictability of EURO STOXX returns

This table presents the estimation of equations (6), (7) and (8). The dependent variables are returns of the EURO STOXX index and of EURO STOXXX index futures. Independent variables are changes in Google search index (*abn_google*), positive changes in *abn_google* (*abn_google*$^+$), negative changes in *abn_google* (*abn_google*$^+$), square changes in Google search index (*abn_google*^{2}), *abn_google* is defined in equation (1). M^{high} and M^{low} are dummy variables that indicate if the stock index breaks through a 52-week high or a 52-week low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicates if the price of the stock index is in the 3% range of a 52-week high or a 52-week low, respectively. The sample period runs from 2006:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients.

	Panel A: EURO STOXX index returns $r_{M,t}$							Panel B: EURO STOXX futures returns $r_{Fut,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
abn_google_{t-1}	-0.031		-0.007	-0.007	-0.008	-0.007	-0.007	-0.034		-0.008	-0.008	-0.008	-0.008	-0.007
	(0.040)		(0.506)	(0.504)	(0.445)	(0.504)	(0.534)	(0.042)		(0.484)	(0.482)	(0.466)	(0.482)	(0.544)
$abn\_google^{+}_{t-1}$		-0.052							-0.057					
		(0.004)							(0.005)					
$abn\_google^{-}_{t-1}$		0.016							0.018					
		(0.372)							(0.336)					
$abn\_google^{2}_{t-1}$			-0.022	-0.022	-0.016	-0.022	-0.015			-0.024	-0.024	-0.017	-0.024	-0.014
			(0.001)	(0.001)	(0.023)	(0.001)	(0.279)			(0.001)	(0.001)	(0.015)	(0.001)	(0.350)
$\hat{\sigma}_{market,t-1}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.665)	(0.378)	(0.330)	(0.327)	(0.526)	(0.391)	(0.533)	(0.636)	(0.344)	(0.320)	(0.313)	(0.439)	(0.382)	(0.541)
$r_{M,t-1}$	-0.245	-0.218	-0.203	-0.205	-0.180	-0.203	-0.179							
	(0.012)	(0.014)	(0.018)	(0.019)	(0.058)	(0.019)	(0.046)							
$abn\_google^{2}_{t-1} \cdot M^{high}_{t-1}$				0.017							0.009			
				(0.721)							(0.853)			
$abn\_google^{2}_{t-1} \cdot M^{low}_{t-1}$					-0.009							-0.010		
					(0.214)							(0.202)		
M^{high}_{t-1}				0.002							0.003			
				(0.777)							(0.613)			
M^{low}_{t-1}					0.014							0.009		
					(0.259)							(0.534)		
$abn\_google^{2}_{t-1} \cdot M^{Range\_high}_{t-1}$						0.031							0.030	
						(0.437)							(0.465)	
$abn\_google^{2}_{t-1} \cdot M^{Range\_low}_{t-1}$							-0.008							-0.012
							(0.596)							(0.490)
$M^{Range\_high}_{t-1}$						-0.002							-0.002	
						(0.731)							(0.731)	
$M^{Range\_low}_{t-1}$							0.010							0.008
							(0.275)							(0.378)
$r_{Fut,t-1}$								-0.267	-0.237	-0.222	-0.224	-0.211	-0.222	-0.196
								(0.009)	(0.011)	(0.013)	(0.013)	(0.037)	(0.013)	(0.030)
Constant	0.002	-0.001	-0.007	-0.008	-0.006	-0.007	-0.006	0.003	-0.002	-0.008	-0.008	-0.007	-0.007	-0.006
	0.812	0.852	0.358	0.354	0.463	0.472	0.462	0.770	0.850	0.357	0.344	0.411	0.471	0.485
Observations	239	242	239	239	239	239	239	239	241	239	239	239	239	239
R^2	0.123	0.178	0.212	0.213	0.222	0.213	0.218	0.137	0.198	0.236	0.236	0.242	0.236	0.241

Table X
Web Search queries and predictability of implied volatility of the EURO STOXX index

The dependent variable is the implied volatility of the EURO STOXX index ($\hat{\sigma}_{market}$). This table presents the estimation of equations (6) and (7). Independent variables are changes in Google search index (*abn_google*), positive changes in *abn_google* (abn_google^{+}), negative changes in *abn_google* (abn_google^{+}), square changes in Google search index (abn_google^{2}), *abn_google* is defined in equation (1), EURO STOXX index returns r_M. M^{high} and M^{low} are dummy variables that indicate if the stock index breaks through a 52-week high or a 52-week low, respectively. M^{Range_high} and M^{Range_low} are dummy variables that indicates if the price of the stock index is in the 3% range of a 52-week high or a 52-week low, respectively. The sample period runs from 2006:01 through 2011:06. The observations are weekly and returns are in EUR. All independent variables are lagged 1 week. p-values in brackets under coefficients.

	$\hat{\sigma}_{market}$					
	(1)	(2)	(3)	(4)	(5)	(6)
abn_google_{t-1}	0.155		0.158	0.180	0.162	0.079
	(0.000)		(0.000)	(0.000)	(0.000)	(0.075)
$abn\_google^{+}_{t-1}$		0.158				
		(0.004)				
$abn\_google^{-}_{t-1}$		0.153				
		(0.007)				
$\hat{\sigma}_{market,t-1}$	0.029	0.029	0.028	0.030	0.028	0.028
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{M,t-1}$	1.219	1.232	1.270	1.126	1.261	1.057
	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)	(0.000)
$abn\_google_{t-1} \cdot M^{high}_{t-1}$			-0.291			
			(0.000)			
$abn\_google_{t-1} \cdot M^{low}_{t-1}$				-0.173		
				(0.324)		
M^{high}_{t-1}			0.034			
			(0.285)			
M^{low}_{t-1}				0.080		
				(0.467)		
$abn\_google_{t-1} \cdot M^{Range\_high}_{t-1}$					-0.130	
					(0.136)	
$abn\_google_{t-1} \cdot M^{Range\_low}_{t-1}$						0.132
						(0.015)
$M^{Range\_high}_{t-1}$					-0.092	
					(0.000)	
$M^{Range\_low}_{t-1}$						0.035
						(0.288)
Constant	2.457	2.445	2.482	2.438	2.519	2.463
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	239	242	239	239	239	239
R^2	0.842	0.842	0.851	0.845	0.854	0.849