Capturing Investor Attention – Do pre-IPO Google Searches Predict Stock Performance? Evidence from Europe

Valtteri Torikka

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Abstract

The amount of investor attention has been found to affect stock returns. Recently, a novel and unique attention measure – the volume of Google searches – has been found to predict IPO returns in the US market (Da et al., 2011). This study brings insight on the same issue and confirms that similar dynamics prevail in the European markets. Using search volume indices from Google Trends as the main explanatory variable, I study a sample of 254 IPOs from the beginning of 2004 to the late 2015 by various controlled cross-sectional regressions and robustness checks. I find that search volumes can predict IPOs' first-day returns significantly and show signs of predicting long-term returns in continental European markets. The results of this study are mostly in line with attention-induced price pressure hypothesis by Barber and Odean (2008) that suggests that stocks that gather an unusually high amount of attention experience a positive short-term price pressure accompanied by long-term price reversal.

Aalto University School of Business

Department of Finance

Thesis instructor: Matthijs Lof

Aalto University
School of Business

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1. Introduction

In the contemporary world where internet search volume information is easily accessible by virtually anyone and is more valuable than ever, it has become relevant to ask the question, whether search volumes possess the power of prediction. Internet searches have been found to predict various economic phenomena in the recent past but have yet remained fairly unused in the field of finance and more precisely, in the field of IPOs.

A paper concerning the US stock market – studied by Da et al (2011) – found that Google search volumes can predict IPO stock returns. However, no extensive research has been done on this question considering continental European markets. Inspired by the paper *'In search of attention'* by Da et al. (2011) I study the effect of the volume of pre-IPO Google searches on a company name on their IPO performance with empirical evidence from the largest continental European stock exchanges.

The contribution of this study is the insight on the behavior of European IPO stock returns within the framework of investor attention represented by Google search volumes. I find that an increase in Google search volumes prior to the company's IPO predicts significantly temporary positive stock price pressure in the short term, but cannot sufficiently explain returns in the longer term, although providing some indications of predictability.

Background of the study

The background of my study lies in the context of Efficient-Market Hypothesis (EMH) and deriving from that: investor attention. As widely known, the semi-strong-form of EMH implies that all new public information should transfer into share prices with no delay (Fama, 1970). It seems though that retail investors pay different amounts of attention on different stocks and particularly on different IPOs (Ritter and Welch, 2002). This implies that the information on different stocks is transferred into stock prices at unequal pace. Variance in the promptness of information transfer into stock prices thus creates a state of inefficiency.

In this study I test whether the attention-induced price pressure hypothesis by Barber and Odean (2008) holds true in the European IPO markets, as Da et al. (2011) have found it to be in the US markets. Attention-induced price pressure hypothesis suggests that retail investors tend to be net buyers of stocks that gather a lot of attention. Therefore, an increase in retail investors' attention should result in temporary positive price pressure on a particular stock.

Moreover, the effect should reverse and attention-grabbing stocks should experience a price reversal in the long-run and even underperform the less popular stocks (Da et al., 2011).

Whereas many indirect proxies of attention have been formulated in the past, the first direct measure of investor attention was introduced in 2011 in the study by Da et al. They show that Google search volume represents an indicator that undeniably captures attention. The goodness of Google searches as a measure is largely based on its popularity, since Google continues to be the most used internet search engine.[1] Direct measurability of attention by Google searches is also justified by reason: if you search for a term from Google, you are unambiguously directing attention to it. Da et al. (2011) also show that Google searches indeed capture the attention of retail investors differentiating them from institutional investors, that find their information through more sophisticated systems. They also show that search volume is different from but correlates with former indirect measures of attention. Moreover, since no trading information exists prior to a company's IPO, Google searches present a one-of-a-kind possibility to test the effect of retail attention on IPO returns.

Google Trends

Google Trends is a public Google Search –based analysis tool that allows users to obtain search volume data free of charge. Google Trends was launched in 2006 and it contains search volume data from 2004 for various languages and different regions. Google Insights for Search was introduced in 2008 and provided a significant improvement in the usability and reliability of Google search data. In 2012 Insights was merged into Google Trends.

Search Volume Index (SVI) is an indexed and normalized measure of Google search volume on a chosen search term provided by Google Trends. It takes values between 0 and 100 and is relative to the chosen time period. For example, if one chooses the time period from 2004 to 2016, the week with the highest search volume takes the SVI value of 100. If then one chooses e.g. 1.1.2015 – 31.12.2015 as the time period, there is also in this case one point in time where the SVI takes the value of 100. The value of SVI is hence always comparative to the chosen time range. SVIs are easily importable as CSV-files which makes it very user-friendly to obtain and handle the data. The main explanatory variable of this

[1] http://gs.statcounter.com/#all-search_engine-ww-monthly-201508-201608 (14.10.2016)

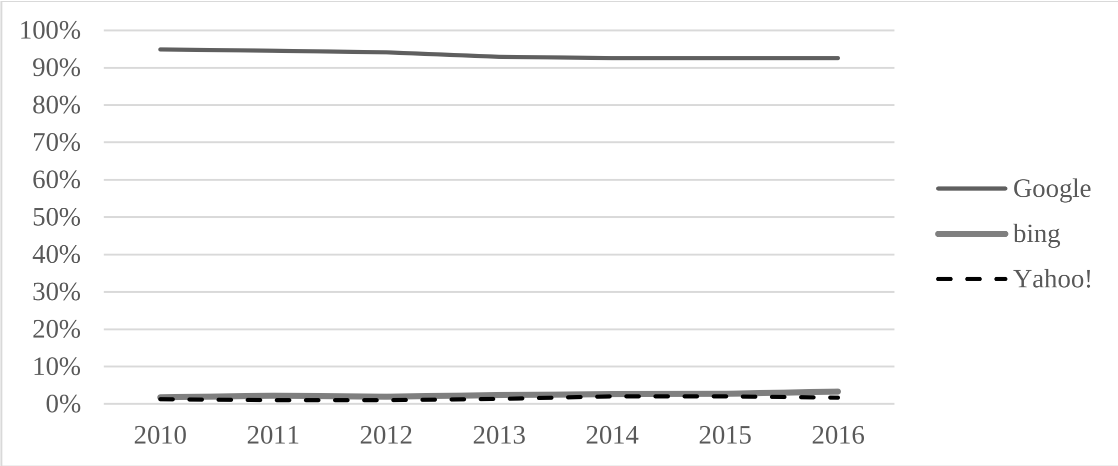

Figure 1. The three most popular search engines in Europe by market share (2010 - 2016)[1]. Google search has sustainably kept its undisputed search engine market leadership with over 92% market share in Europe since 2010 and has been the market leader since 2002. The second and third largest search engines – Bing and Yahoo! – together form only 5 % of the total market share. (Googlepress News Announcements, 05/2002, link to the website in the references).

study – ASVI (Abnormal Search Volume Index) – is constructed from SVI values prior to and within the week of the company's IPO. ASVI is defined more accurately in the data-section.

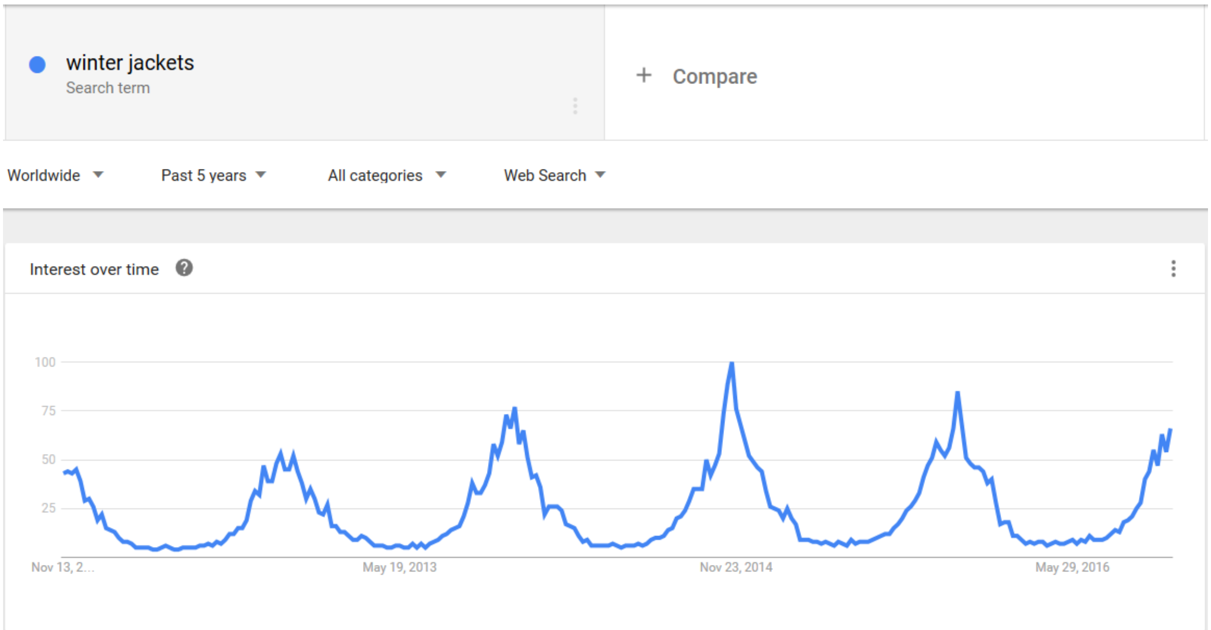

Figure 2. SVI trend of the search term "winter jackets".

The figure plots the worldwide search volume index development for the search term "winter jackets" within the past five years. On the y-axis is are the values for SVI's and on the x-axis the time. It is easily noticeable that the trend is very seasonal and very apparently related to the winter season. Source: Google Trends (see references).

Hypotheses and overview of findings

The objective of this study is to find out whether Google search volumes have predictive power regarding IPO returns in continental Europe. The time ranges of the study are determined according to the study by Da et al. (2011): short term is defined as first-day return and the long term as the return between weeks 5 and 52. SVI (Google Search Volume Index) functions as the main explanatory variable.

The hypotheses are formed as follows:

H1: *SVI contributes to large IPO first-day return.*
H2: *SVI contributes to long-run IPO underperformance.*

Using Abnormal Search Volume Index (ASVI) as the main explanatory variable in various cross-sectional regressions, I find that the hypothesis by Barber and Odean (2008) can be partly confirmed in the European markets: the level of ASVI before the company's IPO positively predicts the first-day returns of the stock, but discontinues to fully explain the returns within a year of the IPO. There are indications of the long-term predictability, but they cannot be confirmed to be robust. The non-parametric Wilcoxon test reaches a p-value of close to the 10 % significance level (0.101) on testing the return difference of low-ASVI and high-ASVI stocks. Also, if ASVI alone is regressed on the long-term returns after a 90 % winsorizing, it gains a significant negative coefficient at the 5 % level, which indicates that ASVI could predict long-term underperformance.

To control the results, I use the log of *Asset Size*, *Offering Size* and *Company Age* along with *Secondary Share Overhang* and *Price Revision* as control variables (all variables defined in Table 3). The variable choices are justified by following the practice of Da et al. (2011). Along with ASVI, *Price Revision* and *Log(Offering Size)* seem to explain the results the best.

Firstly, I confirm that the IPO week experiences significantly higher (33 %) search volumes than the eight weeks preceding the IPO. Secondly, I find that stocks with the highest quartile ASVI experience significantly higher first-day returns of 5 % compared to the lowest quartile ASVI stocks. I document a reversal in the long-run returns of the high-ASVI stocks, but cannot confirm it to be significant. After dividing the sample time period in two, I find that the IPOs before 2008 mainly seem to explain the effect, especially in the short term. Post-crisis results show similar direction and magnitude as the pre-crisis results, but due to the very low sample size of IPOs after the crisis, the effect in that time period cannot be confirmed to be significant. In the light of the results, it is however fairly safe to assume that the effect persists in the post-crisis term.

Limitations of the study

The study is limited to examining continental European IPOs only. Other issues and securities in other regions are left undiscovered. The set of control variables is also limited to the ones available in Europe within reasonable effort considering the time constraint of the thesis work. Most of the indirect proxies for investor attention such as the number of published news and investor sentiment are not within reasonable reach in Europe. The control variables are however chosen with the priority of having found to have an effect in the US study by Da et al. (2011).

SVI as a variable holds many weaknesses and is not sufficient at all times. Also its nature of being indexed and normalized makes it difficult to estimate whether the changes in the number of searches are happening on a large or a small scale compared to the sample. The zero-level SVI is left vaguely defined by Google. Also, whether SVI captures individual investor attention in Europe or not is left as an assumption relying on the work of Da et al. (2011), who recognize SVI as a direct measure of individual investor attention. The study does not take a stand on the differences in retail investor cultures of Europe and the US. The time period is limited to begin from 2004, since it is the starting point of SVI data.

The rest of the paper is organized as follows. Section 2 sheds light on the theoretical context of investor attention, existing attention proxies and SVI in literature. Section 3 introduces the sample data, variables and the methodology of the study. Section 4 walks through results with section 5 concluding the study.

2. Literature review

Attention-induced price pressure hypothesis

The base of traditional asset pricing models builds on the assumption that stock prices adapt new information instantly when it is available (Fama, 1970). This assumption clearly further implies, that markets need an adequate amount of attention to be paid to the particular stocks in question. As Kahneman (1973) has quite famously shown, attention is a scarce cognitive resource, which forces investors to select a limited number of options at a time to pay attention to.

Merton's paper from 1987 sheds light on the issues relating to the challenges of perfect market model, the costs of seeking information and the market equilibrium formed on incomplete information. As a pioneer of investor attention research, he introduces the "investor recognition hypothesis" that suggests that individual investors prefer only to buy stocks that they already know (Merton, R., 1987).

Odean develops Merton's (1987) idea and argues in his paper *"Do investors trade too much?"* (1999) that investors are unable to wisely choose stocks from thousands of alternatives and tend solve this problem by buying stocks that have *recently* caught their attention. The attention-induced price pressure hypothesis by Barber and Odean (2008) is an even further developed version of the previous argument, and is explained through the inevitability of limited choices for the individual investors.

As the set of buyable assets for individual investors is vast and they tend to only sell what they own (they very rarely sell short[2]), they are faced with unequal possibilities of buying and selling. Barber and Odean (2008) suggest that since limited attention determines the set of choices, investors tend to more likely buy stocks that grab their attention than the ones that do not. Therefore, an increase in retail attention should lead to aggregate net buying from individual investors. This should then create a temporary positive price pressure on the stocks in question, which then should reverse when the pressure eventually clears away.

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[2] Only 0.29 % of all individual investor positions are short (Barber and Odean, 2008). This is also consistent with the finding of Dorn (2009), who shows that long positions in Europe are mostly taken by individual investors whereas short positions are taken by institutional investors.

Investor attention proxies

Investor attention as such is an abstract non-quantifiable phenomenon, that nonetheless drives many other phenomena. To quantify and measure investor attention, some proxies for it are needed.

Number of papers on different proxies for investor attention have been published. Barber and Odean have probably found the most proxies for attention: media attention measured by news (2008), extreme returns (2008) and retail investor trading volumes (2009) all represent significant measures of investor attention. Advertising expenses have found to affect stock returns positively, even after controlling for various other price predictors (Chemmanur and Yan, 2009). The advertising expenses not only seem to affect stock returns but the number of stockholders and better liquidity as well (Grullon et al.). Seasholes and Wu (2007) argue that stocks hitting upper price limits experience higher returns, which however reverse within the following week. Gervais, Kaniel, and Mingelgrin (2001) have also studied the effect of extreme trading activity and have come to the conclusion that high volume return premium exists for as long as a month after the week of unusually high trading volume. Along with studying the effect of trading volume, Hou, Peng and Xiong (2008) find that market state has an effect on the profitability of price momentum strategies. It seems that when investors pay attention to earnings news, the price underreactions are weaker than in the setting of low attention. (Hou et al., 2008).

Along with the study by Da et al., Mondria and Wu (2011) present another novel and very relevant finding relating to attention measured by SVI. What they find is that measured by geographical SVI, local investors tend to pay abnormally high attention to local stocks, and the stocks that gather a lot of local attention compared to nonlocal attention, tend to earn higher returns.

It is very intuitive, that when information is pushed towards investors, they will pay more attention to them. However, news does not necessarily guarantee attention, if investors do not read them, and turnover can also be affected by various other factors than attention (Da et al., 2011). Google search is by definition attention-grabbing, since users actively search information that they are already paying attention to. This makes SVI the first genuinely direct measure of attention.

Google Trends in literature

Google Trends was published a decade ago and it has been utilized vastly in many areas of research since. Already now there are over four million search results on Google Scholar on the search term ‘Google Trends’. Perhaps most famously, search volume indices have been used to estimate influenza-like diseases in epidemiology research. Examples of this include the studies by Polgreen et al. (2008) and Ginsberg et al. (2009), who find Google searches to be a timely and a robust way to predict influenza occurrences. The study by Ginsberg et al. (2009) has even inspired a tool for the use of predicting flu incidence: Google Flu Trends (www.google.com/flutrends/), which speaks for the relevance and predictive power of Google Trends. The findings of the above-mentioned researchers have then further inspired various more recent epidemiology studies as well.

Google Trends has also been used in the field of economics. As a pioneer of web search analytics research, the Chief Economist of Google – Hal Varian (2009) – has shown that search volume data has the power of estimating the activity in different economic phenomena. With H. Choi they bring insight on predicting car part sales, tourism, consumer confidence and initial claims for unemployment benefits (Choi and Varian, 2009). Vosen and Schmidt (2009) examine private consumption and find that Google searches are a better indicator than survey-based methods in predicting retail sales. Guzmán (2011) even suggests that Google could be used as a measure of inflation expectations.

Some research has also been done on the explanatory power of search volumes regarding popularity of institutions and individuals. Vaughan and Romero-Frías (2014) validate that Google search volumes on university names have significant correlation with the university reputation. One of the examples where search volumes have not been able to predict results is a study by Lui, et al. (2011), that finds that search volumes poorly predict election results in The United States.

Generally, Google search volumes seem to have predictive power within numerous contexts and the methodology related to their use has been applied extensively throughout different disciplines.

3. Data and methodology

In addition to Google trends data that is freely accessible by anyone, I obtain the remaining event data from Thomson Reuters SDC Platinum and time series data from Datastream.

Sample

The criteria for the selection of the sample companies are as follows. All companies are found in the SDC Platinum database under the selection of Public Continental European listings, unit issues excluded. Listings are narrowed down to IPOs (first listings in the market) that have occurred between 1.1.2004 and 1.9.2015. The sample size with these criteria is 1262. To increase the feasibility of the sample and availability of the data, only common and ordinary shares are included and REITs (Real Estate Investment Trusts) are excluded. Also the list of companies is restricted to the ones that SDC can identify an ISIN for. This is done to ensure further data availability. Moreover, the exchanges where the companies are primarily traded are limited to the six largest (by market cap) continental European stock exchanges and their predecessors to form a geographically unified and market-wise developed enough sample. London Stock Exchange is left out of the sample because a similar study in the form of a Master's thesis with a broader market sight has been done in Aalto University (Wuoristo, L., 2012). Wuoristo has confirmed that Google search volumes have predictive power on FTSE AllShare index stocks' returns in the UK market. Even though Wuoristo has not examined IPO returns, I find it relevant to concentrate on the yet undiscovered European continental markets.

Even though for example the Euronext exchange was formed in 2000 in collaboration with Belgium, Portugal, France, and the Netherlands (and UK, though excluded here), and the time series begin in 2004, SDC still shows some listings by the former exchange names. Therefore, also all the preceding exchanges are included in the sample. The viable sample size with above mentioned criteria is finally 332.

Table 1. Large European stock exchanges by domestic market capitalization in USD millions (December, 2015).

The table contains the ten largest stock exchanges in Europe. The IPOs of the six biggest stock exchanges (LSE Group ignored) are included in the sample (underlined below.) [3]

Exchange	Market cap ($)
LSE Group	3 878 774
Euronext	3 305 901
Deutsche Boerse	1 715 800
SIX Swiss Exchange	1 519 323
Nasdaq Nordic Exchanges	1 268 042
BME Spanish Exchanges	787 192
Oslo Bors	193 896
Warsaw Stock Exchange	137 770
Irish Stock Exchange	128 009
Wiener Borse	96 079

SVI data

I gather the SVI data from the week of the IPO and eight weeks before the IPO week. The data is collected by hand from https://www.google.fi/trends/ by first defining the search term and then the time range (the dates between which the SVI's are gathered). As Google offers only daily data for the nine-week period, weekly SVI's are calculated by the mean of each day's SVI. Google trends data exists since 2004 and therefore is the beginning point for my data set.

Because the shares of the companies have obviously not been traded publicly prior to their IPOs, they do not have tickers or any similar codes widely known or available with which investors could have had distinctively searched for them in the purpose of investor attention. Therefore, the search term for each company is determined individually. In most cases, the company name is the viable search term. In some cases, where the company has a very long name that is commonly shortened in public use, the viable search term is the

[3] http://www.world-exchanges.org/home/index.php/statistics/monthly-reports. (December 2015). Exchanges included (as stated in SDC): Amsterdam, Berlin, Brussels, Copenhagen, Euro Paris, Euronext AM, Euronext B, Frankfurt, Helsinki, Madrid, Milan, OMX Copenhagen, OMX Helsinki, OMX Stockholm, Oslo, Paris, Stockholm, Swiss Exchange, Zurich. Milan (Borsa Italiana) is included since it is a large continental exchange even though it became a subsidiary of LSE Group in 2007.

abbreviation of the company's name.[4] Also abbreviations like "AB", "SA" or "AG" stating the company type preceding or following the company name are left out in most cases.

A problem with so-called "noisy" company names exists. Some company names like *Bluewater, CAM* or *Mondo* ("world" in Italian) are by nature common terms that can be associated with a variety of different meanings besides the companies in question. The company-type specifying abbreviations are left to the search terms in these cases to distinguish them from the general meanings.

Abnormal Search Volume Index (ASVI) is the main explanatory variable of the study. ASVI is calculated as follows:

$$ASVI = log(SVI)\_t\ ) - log[Med(SVI)\_(t-1), \ldots, (SVI)\_(t-8)\ )] \qquad (1)$$

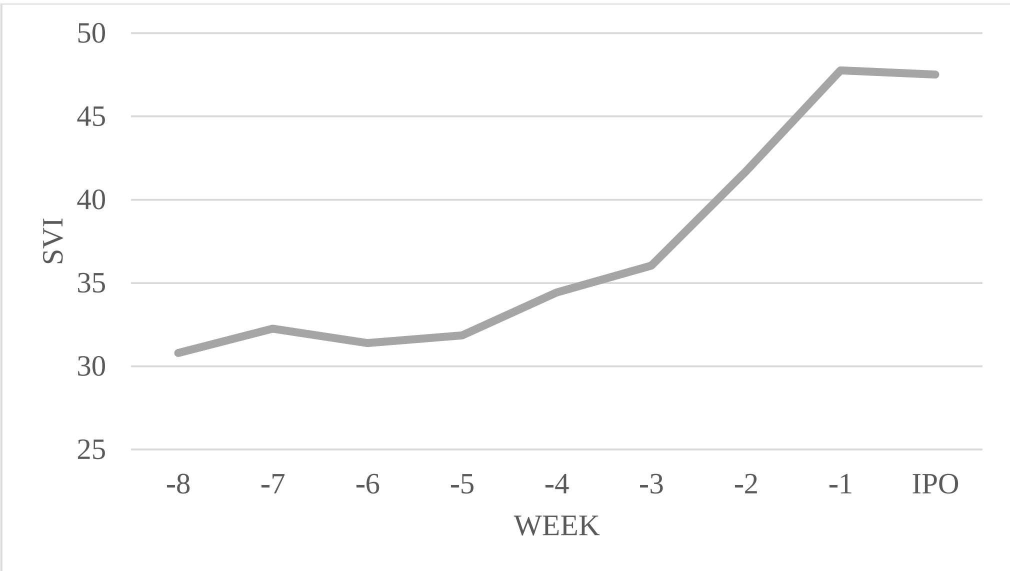


Figure 3. Sample mean SVI development prior to the IPO.

It is clearly visible that the search volume on a company name increases steadily before the IPO week peaking at one week prior IPO with slight decrease on the IPO week. The IPO week experiences significantly higher (32.8 %) search volumes than the eight weeks preceding the IPO. After excluding insufficient SVI data from the sample, the viable sample contains 291 search terms. The exclusion procedure is further described in this section.

One problem with the Google's SVI data is that SVI does not tell us what the actual number of searches has been within the specific time periods. SVI only reveals the indexed

[4] For example: the search term for *Bergesen Worlwide Gas ASA* is *BW gas.*

and normalized development of the search volume on a specific term. There is obviously variance – quite possibly a very high variance – within the volumes of the searches done on different company names. Therefore, in the case of a company that is searched for very little, a big change in a relatively small number of searches should not necessarily have a large effect on total attention of the firm. However, SVI captures this change and it is impossible to balance out the effect with the limited information that SVI offers. Also, as SVI is normalized, it makes it hard to estimate what Google considers as the "zero-level" of searches. Google gives very vague definitions of this on their website.[5] Due to this uncertainty, to make the sample more accurate, I exclude from the sample all the queries where more than 50 % of the daily SVI's are zero. I identify 32 of these company names. There are also 9 search terms with no SVI data at all. After these corrections the sample size is 291. Sufficient return data is available for 254 of these companies.

Table 2. The final sample size and the phases of its formation.

The IPOs date between 1.1.2004 and 1.9.2015.

Data	Volume
Public Continental European initial offerings (unit issues excluded)	1262
Listings of six largest exchanges (only common/ordinary shares, REITs excluded, ISIN available)	334
Companies with unfeasible SVI data	43
Companies with unavailable return data	37
Final sample size	**254**

Dependent variables

The research is divided into two parts regarding the time period of the returns. I follow the choices of Da et al. (2011) in the scaling of the time ranges. First, I examine the relation between IPO's first-day returns and ASVI. Secondly, I look at the longer term returns in relation to ASVI. The longer term is defined by Da et al. as the cumulative abnormal return

[5] https://support.google.com/trends/answer/4365533?hl=en&ref_topic=4365599 (10.11.2016)

between weeks 5 and 52 after the IPO. However, simple regression results of ASVI's effect of monthly cumulative returns are also reviewed in the results-section.

First-day returns are calculated simply as the price change between offer price and the first available closing price of the stock, whereas the long-run abnormal returns are calculated from the cumulative monthly returns. The definition of the abnormal returns is further explained in the following paragraph.

As I study returns occurring only shortly after the IPO (the longest studied period is twelve months after the IPO), there is no suitable asset pricing model for my purposes to calculate abnormal returns. This is of course due to the lack of historical return data on my sample companies. Therefore, I adjust the monthly returns with industry returns, as Da et al. (2011) have also done in one of their regression sets.

The industries are identified by 4-digit SIC codes, that I obtain from Datastream with lists of ISINs that I gather from the different stock exchanges' websites. To get large enough industry portfolio sizes, the 4-digit SIC codes are then reduced to 2-digit codes that express a broader industry definition. The sample companies are then also assigned a 2-digit SIC code deriving from the 4-digit one. Every sample company's returns are then compared to the industry at the specific time of the IPO. The industry sample contains 2478 companies listed in the largest European stock exchanges between 2004 and 2016.

Sample companies' monthly returns and industry returns are calculated with the Datastream variable RI (Return Index) that is defined as follows: "Return index (RI) shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date." Although RI does not bring much added value as a measure to the calculation of returns compared to simple price development, it takes into account possible exceptional dividend practices within the sample companies.

The returns are calculated as the percentage development of RI's beginning four weeks from the IPO and ending at 52 weeks from the IPO. The first month is left out of the long-run return horizon because retail attention seems to revert largely four weeks after the IPO, as shown in Da et al. (2011).

RI (Return Index)

$$RI_t = RI_{t-1} \times \frac{PI_t}{PI_{t-1}} \times \left(1 + \frac{DY_t}{100} \times \frac{1}{N}\right) \qquad (2)$$

Where:

RI_t = return index on day t

RI_{t-1} = return index on previous day

PI_t = price index on day t

PI_{t-1} = price index on previous day

DY_t = dividend yield % on day t

N = number of working days in the year (taken to be 260)

Control variables

The control variables used in the study are adapted from the paper by Da et al. considering the availability of data and the time frame at hand. In choosing the variables, attention is given to the level of significance they have produced in the reference study. There are five control variables and two additional interaction control variables. All the variable definitions are listed in Table 3.

Table 3. All variable definitions.

Variable	Definition
Dependent variables	
First-day return	Absolute first-day return of a stock. First Datastream available closing price index (PI) divided by 100 minus one (100 represents the value of the offering price).
Cumulative industry-adjusted long-term return	Abnormal cumulative returns between the weeks 5 and 52 after the IPO adjusted by industry returns defined by 2-digit SIC codes. The industry companies are obtained from public stock exchange websites and the returns for the companies are obtained from Datastream.
Independent variables	
ASVI	Abnormal Search Volume Index. The log of SVI during the IPO week minus the log of median SVI during the eight weeks before the IPO. (Da et al., 2011)
Log(Asset Size)	Log of Total Assets of the company prior to the IPO. Obtained from Datastream.
Log(Offering Size)	Log of total number of shares offered in the market multiplied by the offer price in MEUR. Obtained from Datastream.
Log(Age)	Log of number of years between the company's founding year and the year of the IPO. The dates are obtained from SDC.
Secondary Share Overhang	Secondary shares offered divided by the total number of shares offered in the market. Obtained from Datastream.
Price Revision	Ratio of the final offering price divided by the original middle of the filing price range. IPO final offering prices and initial offering price ranges are obtained from SDC.

Sample descriptive statistics

The descriptive statistics concerning all the variables in the study are stated in Table 4. Firstly, the table shows that on average the sample stocks produce positive, but surprisingly low first-day returns (3.4 %). The maximum first-day return of the sample is not extremely high either (55.3 %). The mean of cumulative long-term abnormal returns is slightly negative; within a year of the IPOs, the companies in the sample underperform their industries on average. The finding is consistent with the result of the study by Loughran and Ritter (1995). The phenomenon is also widely acknowledged in other literature as well. The standard deviation of long-term returns is however notably high (48.5 %).

Secondly, it is noticeable that both the mean and the median of ASVI are positive, which means that firms on average are googled more than usual during the week of their IPO. *Price Revision* is lower than one on average, which means that the companies are listed on average with a lower offering price than the middle of the filing price. This finding is consistent with the findings of Ritter (2003), who shows that in Europe IPOs are very rarely priced above the maximum filing price.

Table 4. Sample descriptive statistics.

Variable	Mean	Median	Standard Deviation	Minimum	Maximum	Observations
First-day return	0.034	0.007	0.102	-0.206	0.553	248
Cumulative long-term abnormal return	-0.017	-0.093	0.485	-0.963	2.642	254
ASVI	0.434	0.300	0.886	-4.079	3.181	254
Secondary Share Overhang	0.342	0.000	0.413	0.000	1.000	251
Log(Offering Size)	17.046	17.416	2.321	8.124	21.609	251
Log(Asset Size)	12.609	12.511	2.315	6.759	19.943	224
Price Revision	0.764	0.771	0.083	0.567	0.944	157
Log(Age)	2.508	2.398	0.982	0.000	4.466	160

Methodology

The methodology contains cross-sectional multiple regressions on the short- and long-term returns constructed with various combinations of explanatory variables as well as a robustness check by dividing the time period into two. The robustness is also verified by comparing the returns of low-ASVI and high-ASVI stocks and tested with t-tests and non-parametric Wilcoxon tests. A statistically significant relation between abnormal stock returns and abnormal level of Google searches within the short-term is found in addition to the insignificant results within longer term. Some of the robustness checks however indicate ASVI's possible explainability of the long-term returns.

Table 5. Methods used to test hypotheses.

The table describes the methods to test the two hypotheses of the study.

	Multiple cross-sectional regressions
H1	The relation between ASVI and first-day returns (also with sample winsorized)
H2	The relation between ASVI and long-term returns (also with sample winsorized)
H2	Simple regressions on the monthly cumulative abnormal returns of months 1 … 12 after the IPO
	Robustness checks
H1 & H2	T-test and non-parametric Wilcoxon test on the difference between high-ASVI and low-ASVI stock returns
H1 & H2	Regression by dividing the time period into pre-2008 and post-2008

4. Results

Initial review of the long term

As Figure 4 shows, the returns of high-ASVI stocks begin to underperform the low-ASVI stocks already two months after the IPO and continue to do so even a year after the IPO. Within the first months after the IPO, both high- and low-ASVI stocks seem to perform well compared to their industries, but quickly after the 7th month the high-ASVI abnormal returns begin to drop. The high-ASVI stocks lose to their industry returns within a year, as the yearly cumulative industry-adjusted returns drop to -3.8 %. Low-ASVI stocks perform better by the end of the year producing 1.1 % cumulative abnormal returns. Long-term IPO underperformance is a widely acknowledged phenomenon in literature and is not unusual. Explanations for the underperformance are numerous but are outside of this thesis' scope.

This initial result indicates that there seems to be a difference between high and low-ASVI stocks in the long-term. High ASVI seems to predict lower returns than low ASVI within a year from the IPO. The latter part of the results-section walks through testing the difference.

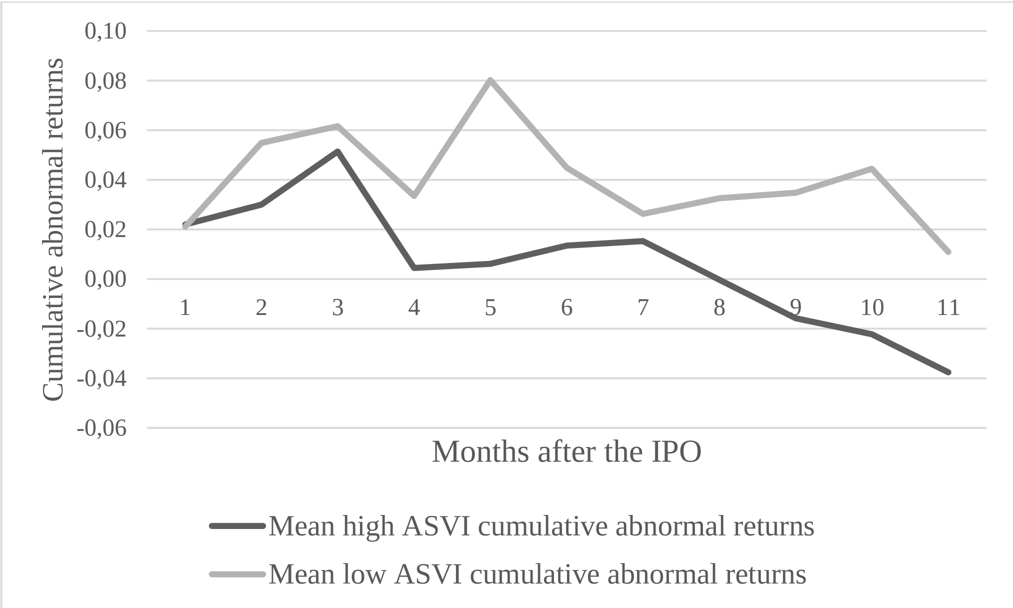


Figure 4. Cumulative abnormal returns on high-ASVI and low-ASVI stocks.

High-ASVI stocks represent the highest quartile and low-ASVI the lowest quartile of the sample ASVIs. Both quartiles contain 65 stocks.

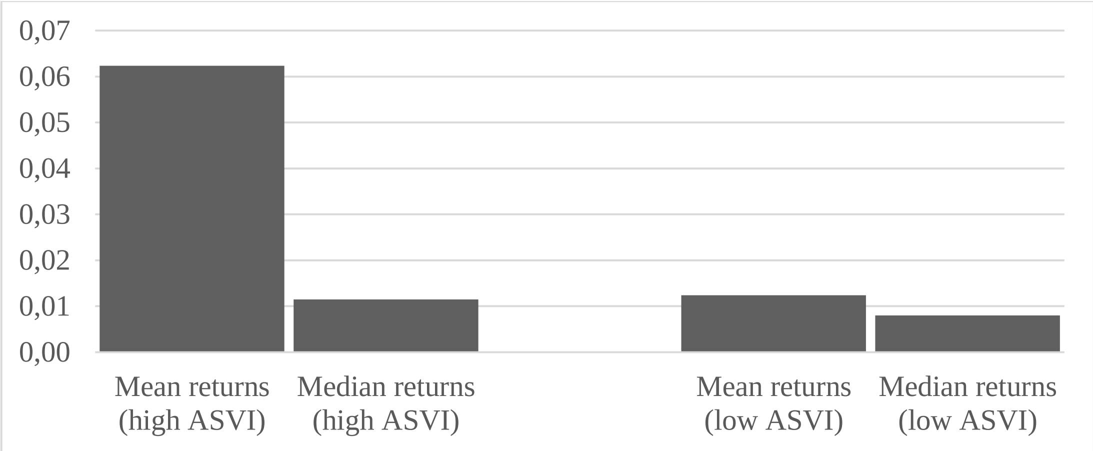
Short term and long term compared

Figure 5 panel A shows clearly, that the mean first-day returns of high-ASVI stocks are higher than those of the low-ASVI stocks. The difference is 5.0 % and t-test confirms that the result is statistically significant at the 1 % level. It is noticeable, that the median of high-ASVI returns is much lower than the mean (5.1 %) and actually even lower than the mean of low-ASVI returns. This indicates that the result is driven by a minority of extremely well-performing IPOs. However, a non-parametric Wilcoxon test confirms that the result is statistically significant at the 10 % level, so the extreme performers do not hold all the effect in them.

Panel B shows that 52 weeks after the IPO the high-ASVI stock returns have reverted compared to the low-ASVI stocks and underperform them by as much as 13 % in absolute returns. Possibly due to a very large variance in especially low-ASVI returns (64.8 %), t-test cannot find the difference significant. The Wilcoxon test result is also insignificant, although the p-value is very close to the 10 % level (0.101), consequently proving that some explanatory value within ASVI exists.

Seemingly the price pressure produced by high ASVI reverses within a year, even though it cannot be confirmed by a t-test.

Panel A. Pre-IPO ASVI and average first-day IPO returns.



Panel B. Pre-IPO ASVI and average long-run IPO absolute returns.

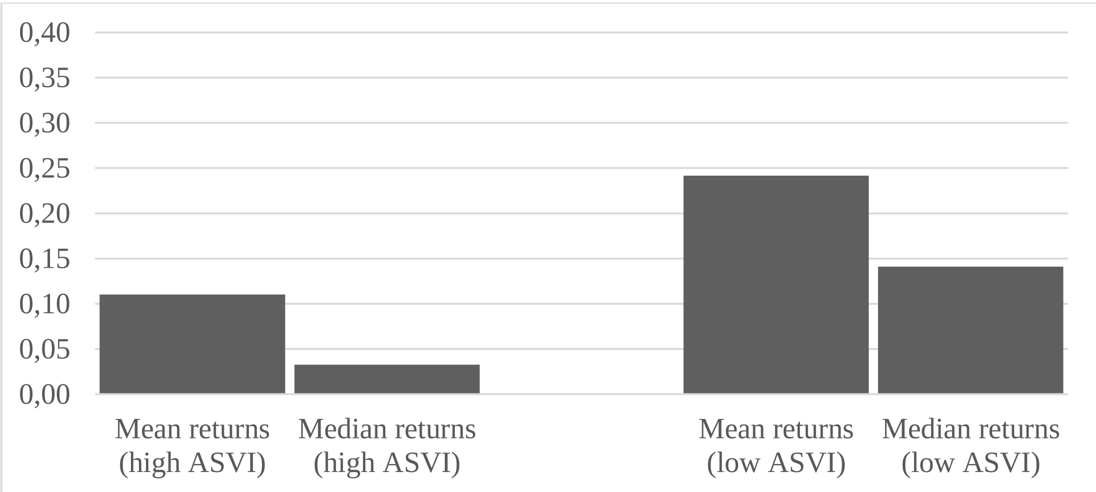


Figure 5. Pre-IPO ASVI, average first-day IPO returns and long-run absolute IPO returns.

The long-run returns represent the IPO stock returns from week 5 to week 52 from the IPO. Notice the different scaling of the charts.

Cross-sectional regressions

From the regression Table 6 we can see that ASVI remains the only variable along with *Price Revision* that continues to explain the first-day returns at the 1 % or 5 % level. *Price Revision*, which is defined as offering price divided by median of filing price, alone explains the variance in first-day returns with adjusted R^2 of 3.7 %. Along with *Log(Offering Size)*, it is the best single explainer of the return variance. The result is consistent with the study by Hanley (1993), which suggests that a bigger revision of the offering price compared to the filing price predicts higher first-day returns. *Log(Offering Size)* is also a strong explainer in regression 3, where no other factors are controlled. The return variance is best explained by the regression where every variable is taken into account (R^2 of 13.1 %).

In the regressions where ASVI is included, its coefficient varies from 0.021 to 0.030. Even after controlling for all other variables, one standard deviation (0.886) increase in ASVI results in 2.39 % (=0.886 × 0.027) increase in first-day returns. ASVI clearly seems to be a very strong predictor of first-day returns; even after a 90 % winsorizing ASVI maintains its significance at the 1 % level.

Secondary Share Overhang and *Log(Age)* seem to be rather weak explainers of the first-day returns, whereas *Log(Asset Size*) of the company turns out to have significant effect in the last regression. However, the effect is negative and very close to zero.

Table 7 shows us the summary of the results of independent variables regressed on the long-term returns. It is immediately evident, that almost none of the variables show significant difference in any direction. ASVI coefficient itself takes negative values in all but one regression – which is in line with previous research – but is unable to produce significant difference in any of them. Contrary to the results of the study by Da et al. (2011), the interaction variable *Price Revision* × *First-day return* does not represent any significance and produces positive coefficients in all but one regression (7).

In the simple regressions where ASVI is regressed on monthly cumulative abnormal returns for months 1 to 12 after the IPO, ASVI loses its explanatory role already after the first month. ASVI does not show any significant effect on the cumulative returns during the first year of the IPO, but the coefficient does turn to negative after the 12^{th} month (-0.011). The result is however not even near significant (t-stat of -0,308).

Interestingly, when ASVI alone is regressed on the 12-month abnormal cumulative returns after a 90 % winsorizing, it gains a significant coefficient of -0.091 at the 5 % level, which implies that ASVI would predict long-term underperformance. This result is however not controlled. It can be concluded that ASVI along with the control variables are not directly able to predict long-term returns of the European IPOs but show some signs of return predictability.

One possible explanation for the low explanatory level of ASVI on the long-term returns might be the very high deviation of the long-term IPO returns within the sample. As seen in Table 4 (descriptive statistics) the standard deviation of the long-term abnormal returns is 48.5 %. The high deviation is likely contributed by the fragmentation of European markets, since Europe is not financially a very coherent area like USA, where the effect exists (Da et al., 2011). Every country has its own regulation, investor culture and level of financial activity.

In my sample, Belgian companies do best in the long-run with mean abnormal returns of 4.2 % (N = 90), whereas Finnish companies lose to their industries by 20.3 % (N = 13) within a year of the IPO on average. The finding is consistent with the findings of European Capital Markets Institute's paper *'A survey of the European IPO market'* from 2006, that records high variance between different European countries long-term IPO returns. The paper also indicates that the IPO return variance is explained by the variance of returns between industries as well. In my sample this issue could have been solved by using industry-clustered standard deviations, but as the industry sample size leaves too little comparable companies in most industry classes, the result would have likely been more biased than in the chosen practice.

Table 6. Pre-IPO Abnormal Search Volume Index (ASVI) and IPO First-Day Return.

The table shows the regression results of IPO absolute first-day returns regressed on ASVI and various control variables (Table 3). Nine different regressions are run with different sets of variables. The sample consist of companies with only ordinary and common stock issues. The sample period is from 1.1.2004 to 1.9.2015. Only the search terms with sufficient SVI data are chosen in the sample. Standard errors are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
ASVI	0,021***				0,030***				0,027**
	(0,007)				(0,009)				(0,01)
Price Revision		0,217***				0,256**			0,211**
		(0,082)				(0,102)			(0,092)
Log(Offering Size)			-0,009***				-0,004		0,014*
			(0,003)				(0,004)		(0,007)
Log(Asset Size)				-0,004				-0,001	-0,01**
				(0,003)				(0,004)	(0,005)
Log(Age)					0,003	0,006	0,002	-0,003	0,002
					(0,008)	(0,009)	(0,009)	(0,009)	(0,008)
Secondary Share Overhang					0,027	-0,043*	0,036	0,041*	-0,039
					(0,022)	(0,024)	(0,023)	(0,023)	(0,024)
Constant	0,024***	-0,135**	0,186***	0,079**	0,001	-0,171**	0,081	0,041	-0,27**
	(0,007)	(0,063)	(0,047)	(0,036)	(0,023)	(0,084)	(0,072)	(0,049)	(0,113)
Observations	248	156	245	218	155	104	155	142	98
R^2	0,032	0,044	0,042	0,009	0,077	0,08	0,019	0,023	0,185
Adjusted R^2	0,028	0,037	0,038	0,004	0,058	0,051	-0,000	0,002	0,131

Table 7. Pre-IPO Abnormal Search Volume Index (ASVI) and Post-IPO long-term stock performance.

The table shows the regression results of cumulative industry-adjusted returns during the weeks 5-52 after the IPO regressed on ASVI and various control variables (Table 3). Seven different regressions are run with different sets of variables. The sample consist of companies with only ordinary and common stock issues. The industry adjustments are made based on European stocks that are bundled by 2-digit SIC codes. The sample period is from 1.1.2004 to 1.9.2015. Only the search terms with sufficient SVI data are chosen in the sample. Standard errors are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ASVI	-0,068	-0,063	-0,06	-0,069	-0,054	-0,031	0,047
	(0,059)	(0,06)	(0,06)	(0,059)	(0,054)	(0,055)	(0,06)
Price Revision		-0,421			-0,6	-0,424	-0,32
		(0,526)			(0,505)	(0,511)	(0,507)
Log(Offering Size)			-0,008			-0,006	0,009
			(0,021)			(0,021)	(0,039)
Log(Asset Size)							0,007
							(0,026)
Log(Age)							-0,078*
							(0,04)
Secondary Share Overhang							0,234*
							(0,124)
First-day return	6,726	5,716	6,216				3,652
	(4,488)	(4,667)	(4,603)				(3,924)
ASVI × First-day return	0,255	0,234	0,317	0,218			-0,539
	(0,603)	(0,604)	(0,618)	(0,604)			(0,563)
Price Revision × First-day return	-7,963	-0,421	-7,378	0,462	0,817		-2,814
	(5,679)	(0,526)	(5,81)	(0,807)	(0,613)		(5,043)
Constant	0,033	0,348	0,171	0,031	0,478	0,464	0,056
	(0,051)	(0,398)	(0,368)	(0,051)	(0,383)	(0,469)	(0,601)
Observations	156	156	154	156	156	155	98
R^2	0,029	0,033	0,027	0,015	0,023	0,009	0,126
Adjusted R^2	0,003	0,000	-0,000	-0,000	0,003	-0,010	0,037

To enhance the robustness of the study, four regressions are formed on two time periods within the sample. The regression results are reported in Table 8. 2008 is chosen as the separating year because of the timing of the financial crisis. 2008 also represents the culmination point, after which IPO popularity has dropped dramatically in Europe – of the 254 IPOs in my sample, only 51 (20 %) have made the initial offering after the beginning of 2008. Google popularity as a search engine has also been lower in the pre-crisis years than in the post-crisis years, which could affect the results. In 2006 Google's market share of all internet search engines was just above 60 % globally but has been growing steadily since.[6]

After leaving out *Price Revision* and *Log(Age)* from the independent side of variables to keep the sample size big enough, the post-crisis sample size still remains very small. What is particularly interesting in these regressions, is that at first sight it seems that pre-crisis ASVI explains most of the first-day returns at hand. Before 2008 ASVI shows significance at the 1 % level and has a fairly large positive coefficient (0.024). This is contradictory with the fact that Google was not as popular a search engine before 2008 as what is has been since. It would be intuitive, that Google searches can hold explanatory value only in situations where it represents a popular and a universal measure. Even though the direction, magnitude and standard error of the post-crisis variables (especially the main explanatory variable: ASVI) are similar to the pre-crisis ones, the low number of observations contributes to no significance. It seems however fairly safe to assume that the predictability of first-day returns continues to exist in the post-crisis term.

Neither of the time periods contain ASVIs that could directly explain long-term returns. *Secondary Share Overhang* is the only variable that seems to explain the results in most regressions and has a positive effect on the returns, even in the long term before 2008.

[6] http://www.seoconsultants.com/search-engines/ and http://searchengineland.com/google-worlds-most-popular-search-engine-148089 (17.11.2016)

Table 8. Pre-IPO Abnormal Search Volume Index (ASVI) and IPO returns in the short and long term, divided into pre-crisis and post-crisis periods.

The first time period lasts from the beginning of 2004 to the end of 2007, and the last time period from the beginning of 2008 to September of 2015. The number of observations vary due to the differences in the availability of data points. Standard errors are stated in parentheses. *, ** and *** represent significance at the 10 %, 5 %, and 1 % level, respectively.

	First-day returns 2004-2007	**First-day returns 2008-2015**	**Cum. 12-month abnormal returns 2004-2007**	**Cum. 12-month abnormal returns 2008-2015**
ASVI	0,024***	0,023	-0,022	0,061
	(0,008)	(0,018)	(0,046)	(0,046)
Log(Offering Size)	-0,007*	-0,018	-0,017	-0,005
	(0,004)	(0,011)	(0,026)	(0,031)
Log(Asset Size)	-0,001	0,006	-0,013	0,043
	(0,004)	(0,01)	(0,022)	(0,029)
Secondary Share Overhang	0,040**	0,130**	0,189**	0,193
	(0,016)	(0,047)	(0,09)	(0,135)
Constant	0,142***	0,195	0,409	-0,683*
	(0,054)	(0,127)	(0,337)	(0,367)
Observations	215	31	188	33
R^2	0,088	0,404	0,03	0,239
Adjusted R^2	0,070	0,312	0,008	0,130

5. Conclusions

This study expands the current knowledge about the predictive power of Google searches on the returns of IPO stocks particularly in the European context. The study is inspired by the attention-induced price pressure hypothesis by Barber and Odean (2008) and the study on the predictive power of Google search volumes in the US IPO returns by Da et al. (2011). Barber and Odean (2008) suggest that short-term price pressure in stocks is highly driven by jumps in investor attention, and that the attention-grabbing stocks underperform comparable companies within the long-term. Da et al. (2011) confirm this by using a novel and a direct measure of investor attention – Google search volumes.

Studying a continental European IPO sample of 254 companies, I find that the first-day IPO returns are highly correlated with the abnormal levels of Google searches prior to the company's IPO, even after controlling for various factors and testing for robustness. The abnormal returns of the first year of the IPO are however not that clearly predicted by search volumes. There are some indications of the predictability, but no robust results can be formed on the long-term underperformance of the highly searched IPOs. The price pressure seems to be largely explained by pre-crisis results, but a safe assumption of the explainability of the post-crisis results can be made as well.

In theory, by utilizing the results of this study, one could benefit from buying into IPOs that hold abnormal search volumes and liquidating the position very shortly after the IPO. In practice the procedure would contain numerous possible problems ranging from winner’s curse to transaction costs that eat the abnormal returns.

Search Volume Index (SVI) by Google Trends is a valuable tool in the field of finance and contains endless possibilities for future research. There is room for future research in the subject of whether the behavior of other security returns could also be predicted by Google searches. An area of interesting research would also be to test how different proxies of attention behave in the European markets.

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