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Google Searches and IPO Performance

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Problem Description

The purpose of this thesis is to investigate how Google searches prior to an IPO are related to updates in the IPO stock price before and after the issuance. The problem is investigated as an empirical study, using econometric tools. Analyses and interpretations are founded in previous IPO research and literature.

Preface

This paper serves as the master thesis of Vilde Krogsrud, Kamilla Amalie Ertesvåg Lillefjære, and Ellen Blegen Ween. All authors undertake a Master of Science in Industrial Economics and Technology Management at the Norwegian University of Science and Technology. The research was initiated as a preliminary study during the fall of 2015. Building on this study, the master thesis was conducted in the time period from January to June 2016.

The thesis aims to investigate the relationship between Google searches prior to an IPO and three common IPO phenomena; price revision, underpricing and post-IPO underperformance. The thesis further investigates the relationships between these three phenomena.

We would like to thank our supervisor, Peter Molnár, for helpful guidance and comments throughout the whole year, at any hour of the day.

Trondheim, June 6^{th}2016

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Abstract

We investigate the impact of retail investor attention, measured by Google's Search Volume Index (SVI), on price revision, underpricing and post-IPO performance. We also investigate how these three IPO phenomena affect each other. We find that SVI between filing and initial pricing predicts price revision. Furthermore, we find that IPOs with either a high increase or decrease in Google searches during the filing period experience the highest level of underpricing. Moreover, we find that positive price revisions result in higher underpricing than negative price revisions. Lastly, we do not find any relationship between SVI during the filing period and post-IPO performance. Instead, we find that SCOOP rating, representing expected first-day premium, predicts underperformance. Hence, our results are more in line with the anticipation hypothesis than the attention hypothesis. In addition, we find that IPOs with very high or very low first-day returns underperform other IPOs.

Sammendrag

Vi undersøker hvordan oppmerksomheten private investorer vier en børsnotering, målt ved søkevolumindeksen på Google (SVI), påvirker prisoppdateringer i forkant av utstedelsesdagen, underprising og utviklingen av aksjekursen etter børsnoteringen. Vi undersøker også hvordan disse tre børsnoteringsfenomenene påvirker hverandre. Vi finner at SVI mellom registrering og initiell prissetting predikerer prisoppdateringer. Videre finner vi at børsnoteringer som opplever enten en veldig økning eller veldig nedgang i Google-søk i løpet av registreringsperioden ser den høyeste graden av underprising. Vi finner også at positive prisoppdateringer resulterer i høyere underprising. Vi finner ingen sammenheng mellom SVI i løpet av registreringsperioden og utviklingen av aksjeprisen i etterkant av børsnoteringen. I stedet finner vi at "SCOOP Rating", som representerer forventet premie første dag, har et negativt forhold med aksjeprisens utvikling. Våre resultater er derav mer i tråd med en "forventningshypotese" enn en "oppmerksomhetshypotese". I tillegg finner vi at børsnoteringer med enten veldig høy eller veldig lav avkastning første dag har en tendens til å gjøre det dårligere i etterkant av børsnoteringen.

Contents

1 Introduction

An Initial Public Offering (IPO) is the first sale of stocks by a company to the public. The company, together with the underwriters, decide the offer price of the stocks. The pricing process is challenging, as the IPO firms usually have little or no operating history. In addition, there is no observable market price of the issuing company prior to the IPO (Ibbotson, Sindelar, & Ritter, 1994). The public get very little insight into the pricing process. As a result, pricing of IPOs is one of the most puzzling phenomena in finance.

Due to the difficulties of pricing an IPO, it is typical that IPOs experience several price updates during the pricing process and in the aftermarket. Furthermore, there are two particularly evident IPO pricing characteristics that researchers agree upon (J. R. Ritter, 1991; Loughran & Ritter, 2003, among others). Firstly, many IPOs experience high first-day returns, meaning that IPOs are underpriced on average. Secondly, high initial IPO returns tend to be followed by a price reversal and underperformance in the long-run. Many authors have suggested that these two features of IPO returns are related to behavioral biases of retail investors (J. Ritter & Welch, 2002; Ljungqvist, Nanda, & Singh, 2006; Cook, Kieschnick, & Van Ness, 2006).

Barber and Odean (2008) investigate the buying behavior of retail investors. They find evidence that retail investors are net buyers of attention-grabbing stocks. Attention-based purchases from many retail investors will create an immediate price pressure. This will inflate stock prices temporarily. When the attention dissipated, the price pressure eases. Stock prices are then expected to revert, which will lead to disappointing subsequent returns. IPO stocks are likely to grab investor attention around the time of the issuance. The IPO price patterns can therefore possibly be explained by the attention theory of Barber and Odean (2008).

When investigating the relationship between retail investor attention and IPO phenomena, researchers face a substantial challenge: There are few or no direct measures of investor attention available prior to the IPO. Da, Engelberg, and Gao (2011) suggest that Google Trend's Search Volume Index (SVI) is a direct measure of retail investor attention. They argue that investors will gather company information before investing. Retail investors are likely to gather this information through search engines like Google. Institutional investors are more likely to use other sources, such as Bloomberg. Thus, to the extent that ? (?) are right, Google's SVI offers a unique opportunity to directly measure retail investor attention prior to an IPO.

The objective of this paper is to investigate how SVI relates to the typical patterns seen for price revision, underpricing, and one-year post-IPO performance. We also investigate how these three IPO phenomena affect each other. We review the entire IPO process - from when the issue is filed with SEC, throughout the first year of trading. Assuming that SVI can be seen as a measure of retail investor attention, compare our results to the attention theory of Barber and Odean (2008).

Google made the SVI publicly available in 2004. From then on, it has been used increasingly as a proxy for investor attention for research purposes related to stock markets. Examples are stock returns (Joseph, Wintoki, & Zhang, 2011; Da et al., 2011), volatility (Dimpfl & Jank, 2015), and earnings announcements (Drake, Roulstone, & Thornock, 2012).

The predictive power of SVI on IPOs has only been researched to a limited extent. Da et al. (2011) find that increased Google searches prior to the IPO can explain both underpricing and post-IPO underperformance. They interpret their results to be in line with the attention theory of Barber and Odean (2008). Jiang and Li (2013) and Colaco, De Cesari, and Hegde (2014) have further studied the impact of SVI on IPO pricing, building on the research of Da et al. (2011). Jiang and Li (2013) find that the pre-market SVI positively affects underpricing. Colaco et al. (2014) find that an increase in the SVI between the initial filing and the initial pricing leads to both higher initial valuations and to underpricing. They also find a positive relationship between SVI and price revision.

When investigating the impact of SVI on IPOs, we base our analyses on a sample of 810 IPOs in the US during the time period 2007-2015. As far as we know, we are the only paper that has studied the relationship between SVI and IPOs employing such a large sample. The results of Da et al. (2011) are based on a small sample of 185 IPOs in the time period 2004-2007. We believe such a limiting sample may affect their results, especially for post-IPO performance. By inspecting a large sample, we are potentially able to provide stronger evidence on whether or not SVI predicts price revisions, underpricing, and underperformance.

We find that Google searches prior to an IPO are positively related to price revisions. However, the relationship seems to be twofold. We find that Google searches before the initial pricing have a stronger relationship with price revision than searches during book building. This indicates that price revision, with respect to retail attention, is mostly a result of not having fully incorporated retail investor attention into the indicative price.

We find that IPOs with either a very high increase or very high decrease in Google searches during the filing period experience the highest level of underpricing. To the best of our knowledge, we are the only paper that has found such a non-linear relationship between SVI and underpricing. Note, when only allowing for a linear relationship, we get similar results to the ones of Da et al. (2011).

The non-linear relationship between SVI and underpricing enables us to differentiate between increased and decreased retail attention prior to the IPO. The result for increased retail attention is consistent with the attention theory of Barber and Odean (2008) - the higher the increase in attention, the higher underpricing. The results for decreased retail attention, on the other hand, can be seen in light of Beatty and Ritter (1986) and Ljungqvist et al. (2006). They claim that IPOs characterized by greater uncertainty or higher risk are underpriced to compensate institutional investors.

Moreover, we find an asymmetric relationship between price revision and underpricing. Positive price revisions tend to result in higher underpricing, compared to negative price revisions. Hence, negative information appears to be more fully adjusted for than positive information. This is in accordance with the partial adjustment theory of Benveniste and Spindt (1989). In addition, we find that SVI and price revision affect each other's relationship with underpricing. IPOs with high SVI and positive price revision appear to be underpriced the most. Hence, we suggest that retail attention and price revision should be seen in relation to each other when predicting underpricing.

We find no relationship between SVI and one-year post-IPO performance. Hence, to the extent that SVI is a direct measure of retail attention, the lack of relationship between SVI and post-IPO performance is inconsistent with the attention hypothesis. If SVI's relationship with underpricing was due to retail investors buying stocks that had received more attention, we would expect the stock price to eventually revert, leading to a negative relationship between SVI and post-IPO performance. Instead, we find that SCOOP Rating, representing expected first-day premium, reliably predicts underperformance. Hence, our results are more in line with the anticipation hypothesis than the attention hypothesis. That is, it may seem like SVI is driven by expectations of high first-day returns. Furthermore, we find that IPOs with very high or low first-day returns underperform other IPOs.

The rest of the paper is organized as follows. Section 2 reviews existing IPO literature. Section 3 explains our data. Section 4 presents the analyses and discussion of the results. Section 5 concludes.

2 IPO Literature Review

In this subsection, relevant IPO literature is revised. Existing literature about price revisions is reviewed first, underpricing secondly, and post-IPO performance lastly.

The IPO pricing process begins when the issuing firm announces that they will go public. This is done by filing the preliminary prospectus (S-1 form) with the U.S. Securities and Exchange Commission (SEC). Either in the preliminary prospectus or in amended prospectuses, the company will provide indications of a price range within which they expect the final offer price to be. When the indicative price range is set, the book building period begins. The underwriters and issuers go on a "road show" to collect information about the demand among institutional investors. Depending on the feedback given by the institutional investors during book building, the price can be revised either up or down. Strong investor demand will be considered positive information and result in an upward revision (J. Ritter & Welch, 2002).

The majority of the existing IPO pricing literature focuses on price changes after the offering, rather than before the offer date. Lowry and Schwert (2001), however, examine the entire pricing process. They find that price updates during the filing period are predictably based on firm- and offer specific characteristics known at the time the issue is filed. Significant relations between such characteristics and initial returns have previously been interpreted as supportive of the information asymmetry theory. However, Lowry and Schwert (2001) conclude that it is difficult to similarly explain the predictability of pre-IPO price updates. Furthermore, they find that price updates reflect market movements prior to the initial filing date as well as during the filing period. They conclude that this finding provides additional evidence that all available information is not incorporated into the indicative price range initially set.

The puzzling phenomena of high initial IPO returns have been researched substantially in the IPO literature. However, the literature finds no single clear explanation of the underpricing phenomenon. As it is difficult to find suitable comparable stocks for IPOs, it is challenging to evaluate the accuracy of IPO pricing. It is thereof also difficult to evaluate underpricing. There are mainly two viewpoints regarding the evaluation of pricing accuracy. Some IPO literature uses initial returns as an indirect proxy for pricing accuracy. Others claim that the long-run price better reflects the companies' true values.

Assuming that the short-term aftermarket price reflects the true value of IPO stocks, asymmetric information theories have been developed to explain high initial returns. The information asymmetry theory of Beatty and Ritter

(1986) suggests that issuances characterized by greater uncertainty will tend to be more underpriced. This is to compensate investors for learning the true value of these issuances. Rock (1986)'s asymmetric information model claims that issuers underprice their shares to induce uninformed investors to participate in their offerings. The argument depends upon the existence of a group of investors whose information is superior to that of the firm, as well as that of all other investors. Benveniste and Spindt (1989) propose an information extraction model in which the information about the value of IPO shares is privately held by institutional investors. Voluntary underpricing is the cost issuers have to pay in order to extract this information. Benveniste and Spindt (1989) further develop a partial adjustment theory. The theory suggests that positive information, reflected in positive price revisions, is only partially incorporated into the final offer price. Hanley (1993) confirms the partial adjustment theory. She finds that positive price revisions tend to be followed by higher first-day returns than negative price revisions do. Overall, all these models suggest that positive initial returns are a direct consequence of voluntary underpricing of IPO shares. Such voluntary underpricing has been discussed in most of the existing IPO literature examining initial returns.

Proponents of using the long-run price as an indirect proxy of pricing accuracy argue that excessive first-day return is not a result of pricing the IPO below its true value. Instead, they argue that underpricing is a result of overly optimistic investors. Ibbotson et al. (1994) argue that issuers take advantage of "windows of opportunity" by going public in hot IPO markets caused by investor sentiment. Furthermore, they argue that the IPO stock prices will revert back to their true values in the long-run. This causes the observed long-run IPO underperformance phenomenon. Hence, the IPOs are not underpriced in the sense that they are priced below their intrinsic values. Instead, the price is temporarily driven up by overoptimistic investors. This is supported by the investor sentiment model of Ljungqvist et al. (2006).

Assuming IPO prices in the early aftermarket are driven by sentiment investors, it can be questioned why rational issuers do not take advantage of the potential surplus provided by investor sentiment. Instead, they leave money on the table. Ljungqvist et al. (2006) suggest that because sentiment-driven demand may cease in the aftermarket, holding IPO stocks is risky. To compensate investors for this risk, the stocks must be underpriced. Note that this underpricing is relative to the offer price that could be set if retail investor sentiment was to be fully incorporated into the offer price. That is, the price is not set below the intrinsic value of the IPO stock. Hence, the issuers still gain, despite leaving some money on the table.

Long-run IPO performance is the most controversial area of IPO research (J. Ritter & Welch, 2002). In light of efficient market theories, some researchers argue that once an IPO is publicly traded, it is just like any other stock. Consequently, risk-adjusted post-IPO stock price performance should not be predictable. Others, such as J. Ritter and Welch (2002), line up behind a behavioral point of view. However, they point out that caution is advisable. They show that the long-run performance of IPOs is highly sensitive to both the methodology, sample set, and sample time period.

Several papers have investigated the relationship between underpricing and post-IPO performance, arriving at very different conclusions. Testing the hot market investor sentiment explanation, J. R. Ritter (1991) investigates the relationship between underpricing and long-run performance. He finds that underpricing is negatively, but weakly, related to long-run performance. The relationship is found to be strongest for young growth companies going public during high-volume years. Krigman, Shaw, and Womack (1999) find a positive relationship between underpricing and long-term performance, however only for IPOs that are moderately underpriced. Furthermore, the model of Ljungqvist et al. (2006) indicates that the relationship is not necessarily monotonic. According to Ljungqvist et al. (2006), the relationship is only negative if the probability of a hot market ending is small.

3 Data

We collect all the 1480 IPOs completed on Nasdaq and the New York Stock Exchange (NYSE) between 2007 and 2015. This data is collected from IPOSCOOP. In accordance with Da et al. (2011), only IPOs of ordinary stocks are included. Thus, unit offerings, close-end funds, real estate investment trusts (REITs), American Deposit Receipts (ADRs), and limited partnerships (LPs) are excluded. We also exclude penny stocks, i.e. stocks with a final offer price below $5. This results in an initial sample of 1312 IPOs.

Google Trends provides data on search term frequency back to January 2004. This data is publicly available. Weekly Search Volume Index (SVI) data for each IPO over a period of three years before, through one year after the IPO date was downloaded. When search volumes are low, Google Trends may return missing or incomplete SVI data. As a result, our dataset is further reduced to 880 IPOs. This is elaborated in Section 3.1. Our standardization of SVI allows a maximum filing period of one year. This constraint cause a further reduction of our dataset to 825 IPOs.

The remaining data are obtained from various sources. Post-IPO stock prices were downloaded from Yahoo Finance. When not available on Yahoo Finance, stock data was supplemented from CRSP. The number of shares offered and the number of employees were retrieved from Nasdaq using a regular expressions script in Python. Filing dates, pricing dates, and the initial price range were manually collected from company S-1 forms filed with SEC. Accounting information was obtained from COMPUSTAT. Firms' founding dates were retrieved from Dr. Jay Ritter's homepage. Table 1 defines all the variables used in the paper. Using a distance-based approach, similar to the one employed by Knox and Ng (1998), we identified and removed 15 extreme outliers in total. These were found in the offer price, issuing size, assets, employees, or SVI. The final dataset obtained thus consists of 810 IPOs.

Figure 1 shows how the completions of the 810 IPOs spread throughout the time period 2007-2015. It is clear that the IPO market saw a steep decline during and right after the financial crisis in 2008.

Note that the availability of SVI and stock prices are limited by the downloading date; February 17^{th} 2016. Hence, IPOs completed after February 2015 have insufficient data to analyze one-year post-IPO performance. Thus, our sample consists of 718 IPO when one-year post-IPO data is required.

Table 1: Variable Definitions

Variable	Definition
Variables used in analyses	
SVI	Aggregate search frequency from Google Trends based on company name
ASVI_w	The SVI in week w minus the mean and divided by the standard deviation of the SVIs between two years and one week before S-1 filing
ASVI	The average $ASVI_w$ between the filing date, F and the IPO offer date, O
ASVI^{F-P}	The average $ASVI_w$ between the filing date, F, and the initial pricing date, P
ASVI^{P-O}	The average $ASVI_w$ between the initial pricing date, P, and the IPO offer date, O
Price Rev	Price Revision: Offer price minus midpoint of initially predicted price range, divided by midpoint of initially predicted price range
Price Rev^{Past10}	Previous Price Revision: The average price revision of the previous ten IPOs
Filing period	The logarithm of one plus the number of weeks between the date of filing the S-1 form and the IPO date
Pricing Period	The logarithm of one plus the number of weeks between the date of initial pricing and the IPO date
Price Range	The initial predicted price range for the offer price during the filing period, divided by the price range midpoint
Age	The logarithm of one plus the number of years between the IPO year and the founding year of the issuing firm
Employees	The logarithm of one plus the number of employees in the issuing firm
Issuing Size	The logarithm of offer price multiplied by shares offered
Rating	Rating from IPOSCOOP (IPO Wall Street Consensus of Opening-day Premiums) on first-day premiums. The ratings range from 1 (low premium) to 5 (high premium), and are based on a consensus input from investment professionals
Crisis_{short}	Dummy variable. Equals 1 if the IPO was completed during the financial crisis (2008-2009), and 0 otherwise
Crisis_{1yr}	Dummy variable. Equals 1 if the IPO was completed so that its one-year return will be affected by the financial crisis (2007-2008), and 0 otherwise
R_1	First-day return, from the offer price to the first-day closing price
R_t^{ExMkt}	Excess market return: Post-IPO return between IPO date and day t, R_t, minus the return of the S&P 500 during the same period
R_1^{Past10}	The average first-day return of the previous ten IPOs
R_1^{Past3M}	The average first-day return of the IPOs three months prior to the IPO
$\text{R}_{S\&P500}^{Past3M}$	The return of the S&P500 index from three months prior to the IPO
Variables used for robustness purposes	
ASVI^{log}	The logarithm of SVI one week before the IPO offer date, minus the log of the mean SVI during two years and one week before S-1 filing
R_t^{ExBM}	Excess benchmark portfolio return: Post-IPO return between IPO date and day t, R_t, minus the return of the corresponding size and book-to-market matched benchmark portfolio during the same period

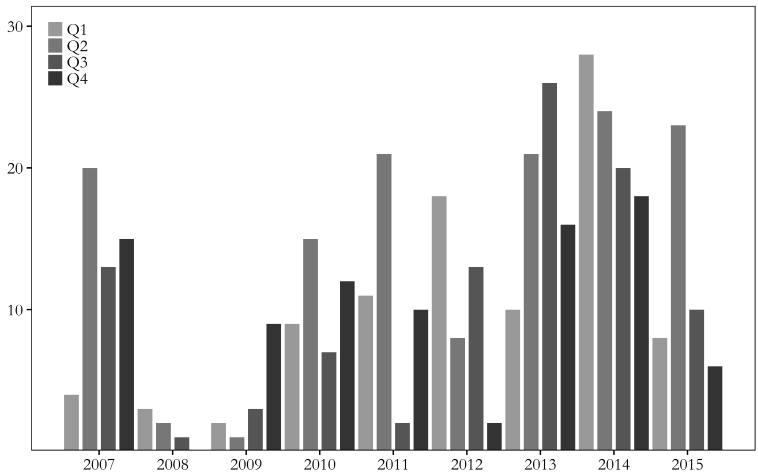


Figure 1: The Number of IPOs Each Quarter, Per Year

The figure plots the number of IPOs completed each quarter from 2007-2015 in the final sample of 810 IPOs

3.1 Google's Search Volume Index

Google Trend's SVI measure the number of searches made for a distinct search term, compared to the total searches made on Google. SVI for a specified time period is further normalized to range within 0 and 100. A value of 100 represents the point in time within the specified time period experiencing the highest search volume, relative to the total search volume. All other values for the search term are scaled relative to this maximum. Hence, SVI values do not represent absolute search volumes. The SVIs for two different search terms are therefore not directly comparable based solely on their index values.

Google Trends returns either daily, weekly, or monthly data. The availability of the three data types depends on the level of the search volume. When a search term is searched frequently enough, daily SVI data can be returned. If not, only weekly or monthly SVI data are available. In order to avoid further significant reductions of our dataset, associated with daily data, we collect weekly SVI data.

If the search volume is below a given threshold, Google Trends may return missing or incomplete SVI data. In these cases, either an empty CSV file or a file with a certain number of values equal to zero is returned. The threshold is currently unknown (Choi & Varian, 2012). We require that no more than 50 %

of the weekly values, i.e. two years (104 values), equal to zero in an IPO's SVI data. Availability of SVI data is the most limiting factor for our sample size. It reduces the number of IPOs from 1312 to 880.

The company name is used as search term. Appendix A.1 contains a synopsis of the 810 company names, i.e. search terms, in our final dataset used for downloading SVI data. Identifying search frequencies by company name may be problematic for two reasons (Da et al., 2011). First, investors may search the company name for reasons unrelated to investing. Secondly, different investors may search the same firm using several variations of its name. However, as tickers are not widely available prior to an IPO, we choose to use company names as search terms. The company names have been slightly adjusted to its most general form by removing terms such as Inc., LP etc.

The SVI data collection of all of the 1312 IPOs in our initial sample was automated with a URL-generating R script. The script takes all the company names as input and download weekly US SVI data into CSV files. The time period used is from three years before, through one year after each IPO date. For IPO's in 2015, the length of available SVI data after the IPO is limited by the time period from the IPO date until the downloading date; February 17^{th} 2016.

There are significant changes in SVI around the time of the IPO. This is illustrated in Figure 2, which plots the mean SVI per week. We observe an increase in Google searches starting about two weeks prior to the IPO. We further observe a sharp peak during the IPO week (week 0). Compared to the SVI data of Da et al. (2011), this is in accordance with what is expected. In order to illustrate the post-IPO SVI throughout one year, we have excluded IPOs happening after February 2015 in the figure. It can be observed that the post-IPO SVI stabilizes at a higher lever than observed pre-IPO. This differs from Da et al. (2011). For their sample of IPOs, the SVI reverts to its pre-IPO level two to three weeks after the IPO.

Da et al. (2011) standardize the SVI in week w by taking the logarithm of SVI during week w and subtracting the logarithm of the median value of SVI during the prior eight weeks. Their standardization is primarily constructed for analyses on stock prices for a sample of Russel 3000 stocks. When applied for IPOs, however, a benchmark period of eight weeks may include important events or announcements about the IPO such as S-1 filing or initial pricing. To omit the effect these events might have on the SVI we choose to standardize differently.

Instead of using a benchmark period of eight weeks prior to the relevant week, we apply a fixed benchmark period from two years before the IPO was

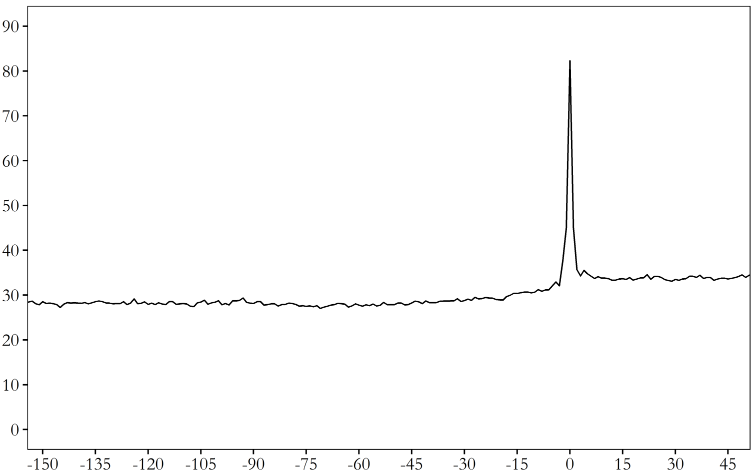


Figure 2: Mean SVI Around IPO

The figure plots the mean SVI per week. The period shown is -155 weeks (three years) before the IPO, through 52 weeks (one year) after the IPO. Week 0 is the week of the IPO. To illustrate post-IPO SVI behavior throughout the first year of trading, a sample period from January 2007 to February 2015 has been used. This results in a set of 718 IPOs.

publicly known, i.e. before S-1 filing, to one week before filing, $F-1$. By doing this, we can capture the increase in the SVI due to the knowledge of an upcoming IPO. The SVI in week w for each company is adjusted by subtracting the average and divide by the standard deviation of the SVIs between two years and one week before the filing week. That is, the adjusted SVI (ASVI) in week w for each company is obtained as follows:

$$ASVI_w = \frac{SVI_w - \frac{1}{104}\sum_{n=F-104}^{F-1} SVI_n}{\sigma_{SVI_{-104\leq w<F}}}, \tag{1}$$

where $w \in [-155, -154, .., 51, 52]$. Week 0 is the week of the IPO, while $w = -155$ and $w = 52$ equals three years prior to and one year after the IPO week, respectively. F is defined as the filing week, where $F \in [-52, -51, ..., -2, -1]$. Note that due to constraints imposed by the downloading date of SVI data, IPOs completed after February 2015 do not have SVI data available one-year post-IPO.

The mean ASVI_w per week is illustrated in Figure 3. The ASVI_w exhibits the same pattern as the raw SVI. The ASVI_w increases by 112% two weeks

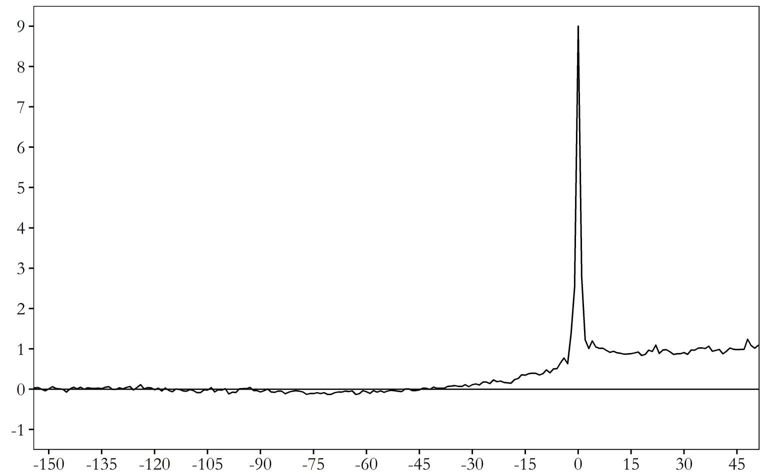


Figure 3: Mean ASVI_w Around IPO

The figure plots the mean ASVI_w per week. The period shown is from -155 weeks (three years) before the IPO to 52 weeks (one year) after the IPO. Week 0 is the week of the IPO. To illustrate post-IPO ASVI behavior throughout the first year of trading, a sample period from January 2007 to February 2015 has been used. This results in a set of 718 IPOs.

prior to the IPO week. During the IPO week, the ASVI_w increases drastically by 241%, compared to the week before. The ASVI_w stabilizes about three weeks after the IPO. It then stabilizes at a higher level than before the IPO.

Da et al. (2011) study only SVI the week before the IPO in their analyses. However, attention given to issuances ahead of the IPO cannot be executed in the act of purchases until after the offer date. Hence, we find it relevant to study the entire time period from after the IPO becomes publicly known, opposed to only one week before the IPO. We are thereby able to include all the attention devoted to the IPO through Google searches. Hence, for the purpose of our analyses, three different average ASVIs are calculated. The filing date (denoted F), initial pricing date (denoted P), and IPO offer date (denoted O) are taken into consideration. That is, the three ASVI variables differ in the time period used to calculated the average across, depending on these three IPO event dates. The time periods used for the three different average ASVIs are illustrated in Figure 4.

The average ASVI for each company during the period between the filing week, $w = F$, and the week before the initial pricing week, $w = P - 1$, is calculated by

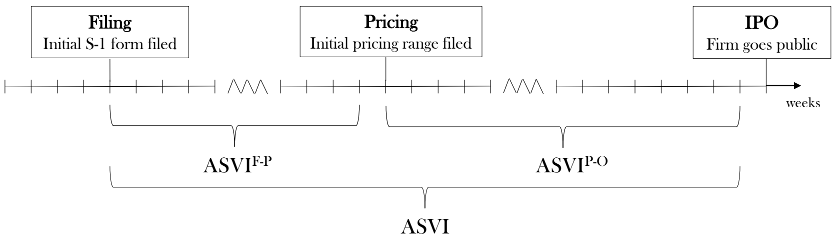


Figure 4: Time Periods Used To Calculate The Three ASVIs
The figure illustrates the time-periods of which the three different average ASVI are calculated across.

$$ASVI^{F-P} = \frac{1}{|P-F|} \sum_{n=F}^{P-1} ASVI_n. \tag{2}$$

The average ASVI for each company during the period between the week of initial pricing, $w = P$, and the week before the IPO, $w = -1$, is calculated by

$$ASVI^{P-O} = \frac{1}{|P|} \sum_{n=P}^{-1} ASVI_n. \tag{3}$$

The average ASVI for each company during the period between the filing week, $w = F$, and the week before the IPO, $w = -1$, is calculated by

$$ASVI = \frac{1}{|F|} \sum_{n=F}^{-1} ASVI_n. \tag{4}$$

To the extent that SVI is a direct measure of retail attention, our three different ASVI represent the average change in retail investor attention during its respective time period relative to the normal level of attention before filing. Positive ASVI values imply an increase in attention. Negative values imply a decrease in attention. Throughout the rest of the paper, this will also be referred to as high or low SVI, respectively.

The ASVIs are used as explanatory variables in our analyses. ASVI^{F-P} and ASVI^{P-O} are applied when investigating price revision, while ASVI is applied when investigating both price revision, underpricing, and post-IPO performance. Descriptive statistics of the three ASVIs for the final sample of 810 IPOs are shown in Table 2.

Table 2: Descriptive Statistics ASVI

The table presents descriptive statistics of the three ASVIs, based on the final sample of 810 IPOs. The values for the sample used to analyze one-year post-IPO performance deviate slightly due to a smaller sample size (718 versus 810 IPOs).

Variable	N	Mean	St. Dev.	Min	Max
ASVI^{F-P}	810	0.82	1.17	−2.52	6.55
ASVI^{P-O}	810	2.40	2.72	−2.31	23.13
ASVI	810	1.12	1.35	−2.03	7.61

3.2 Price Revision

Price revision, in absolute terms, is defined as the difference between the midpoint of the initial indicative price range and the final offer price. The initial price range was manually collected from S-1 forms, while the offer price was collected from IPOSCOOP.

We express price revision in relative terms in our analyses, defined as

$$PriceRev = \frac{S_0 - S_{I.mid}}{S_{I.mid}}, \tag{5}$$

where S_0 and $S_{I.mid}$ denote the offer price and the midpoint of the initial indicative price range, respectively. Thus, positive values for price revision are equivalent with a higher final offer price compared to the initially predicted price.

Price revision, denoted Price Rev, serves as the dependent variable when analyzing price revisions, and as an explanatory variable in analyses regarding underpricing and post-IPO performance. Price revision's descriptive statistics are shown in Table 3. Note that the average price revision is negative and equal to -4.9%. This means that, on average, the final offer price is lower than the midpoint of the initial indicative price range.

Table 3: Descriptive Statistics Price Rev

The table presents descriptive statistics of Price Rev based on the final sample of 810 IPOs. The values for the sample used to analyze one-year post-IPO performance deviate slightly due to a smaller sample size (718 versus 810 IPOs).

Variable	N	Mean	St. Dev.	Min	Max
Price Rev	810	−4.9 %	21.8 %	−70.6 %	100.0 %

3.3 First-Day Return

The first-day return of an IPO is the return on the first day of trading. The offer price and the non-adjusted first-day closing price for all IPOs in our sample are obtained from IPOSCOOP. This data is used to calculate the first-day return for a specific company by

$$R_1 = \frac{S_1 - S_0}{S_0}. \tag{6}$$

Here, S_0 denotes the offer price and S_1 denotes the non-adjusted first-day closing price.

First-day return is used as the dependent variable when analyzing underpricing. An IPO is considered underpriced if the first-day return is positive. If it is negative, the IPO is considered overpriced. First-day return is also used as an explanatory variable when analyzing post-IPO performance.

Descriptive statistics of the first-day returns are presented in Table 4. Our sample has an average first-day return of 16.5%. This is slightly higher than the average first-day return of all IPOs during 2007-2015, which is at 14.0% (J. Ritter, n.d.). The standard deviation is 27.5%, indicating that the sample's first-day returns vary to a large degree across firms.

Table 4: Descriptive Statistics First-Day Return

The table presents descriptive statistics of R_1 based on the final sample of 810 IPOs. The values for the sample used to analyze one-year post-IPO performance deviate slightly due to a smaller sample size (718 versus 810 IPOs).

Variable	N	Mean	St. Dev.	Min	Max
R_1	810	16.5 %	27.5 %	−28.0 %	207.0 %

3.4 Post-IPO Performance

Post-IPO stock prices were downloaded from Yahoo Finance using an automated R script. If stock prices for a company was unavailable on Yahoo Finance, data was manually retrieved from CRSP. Recall that IPOs completed after February 2015 are excluded from the dataset due to the constraint imposed by the downloading date.

The cumulative return for a specific company on trading day t, $t \in [2 : 252]$, is calculated by

$$R_t = \frac{S_t^{adj} - S_1^{adj}}{S_1^{adj}}, \tag{7}$$

where S_t^{adj} is the adjusted closing price on day t.

For the purpose of our analyses of post-IPO performance, cumulative returns are adjusted in two different ways. First, the excess market return is calculated in order to enable comparison between the general market return and post-IPO return. The S&P500 is used as a proxy for the market return. Thus, the excess market return for a specific company on trading day t after the IPO is calculated by

$$R_t^{ExMkt} = R_t - R_{t,S\&P500} \tag{8}$$

Secondly, excess benchmark portfolio returns are calculated in order to enable comparison of post-IPO returns with returns of comparable firms. Scholars (Lyon, Barber, & Tsai, 1999, among others) argue that a simple market index adjustment is subject to biases due to, for instance, new listings and rebalancing. Thus, we create size and book-to-market benchmark portfolios in accordance with Fama and French (1997) and Lyon et al. (1999), among others. We use all companies listed on either NYSE or Nasdaq as reference firms. The data is obtained from Nasdaq.com. We create 45 portfolios, in total. The first five portfolios are based on company size, measured by market value. These are further divided into three portfolios each, based on book-to-market value.

We assume that the portfolio returns are buy-and-hold returns. That is, no rebalancing of the portfolios are performed. We also require that all benchmark companies have been publicly listed for at least two years. This eliminates some of the rebalancing and new listing biases, accordingly. Also, only companies with ordinary shares are included.

The excess post-IPO return, adjusted for benchmark portfolio return, is then calculated by

$$R_t^{ExBM} = R_t - \bar{R}_{t,P_{n,m}} \tag{9}$$

Here, $\overline{R}_{t,P_{n,m}}$ represents the equally weighted average return of the benchmark portfolio corresponding to the IPO company, based on comparable market- and book-to-market values. The initial allocation, based on market value, is represented by $n, n \in [1, 5]$. The secondary allocation, based on book-to-market value, is represented by $m, m \in [1, 3]$.

Figure 5: Average One-Year Cumulative Returns

The figure plots the average cumulative one-year returns for the sample of 718 IPOs used in the post-IPO performance analysis. Raw returns, excess market returns, and excess benchmark returns are illustrated.

Figure 5 shows the raw return of the IPO, and excess market and benchmark portfolio return for day t, $t \in [2 : 252]$. It can be observed that excess market return yields in the lowest return, compared to raw return and excess benchmark return. Also, the one-year performance for both adjustments are positive. Hence, the IPOs in our sample do not underperform neither the market nor the benchmark portfolios after one year, on average.

After the IPO, a lock-up period is imposed on the insiders of the IPO - preventing them from selling their shares. A fall in return about six months into the period can be observed in Figure 5. This might be caused by the lock-up period expiration, which is usually after 120 trading days (six months). At its expiration, there is often a significant increase in supply and hence a decrease in prices.

3.5 Control Variables

For each analyses, we control for several firm-, offer- and market-specific characteristics. Descriptive statistics for these characteristics, based on the sample of 810 IPOs, are shown in Table 5. Note that the reduced sample size for post-IPO performance results in slightly different statistics.

The control variables are defined in Table 1. A brief summary for the reader follows: Filing Period, Pricing Period, and Price Range are considered offer-specific characteristics. The filing period is defined as the time between S-1 filing and the offer date. The pricing period is defined as the time between initial pricing and the offer date. Note that logarithmic values of these variables are used in regressions. Price Range is the indicative price range set in the initial pricing, expressed relative to the price range midpoint.

Table 5: Descriptive Statistics Control Variables

The table presents descriptive statistics for each control variable used in the analyses of price revision and underpricing. The values are raw values. In the analyses employ logarithmic values for Pricing Period, Filing Period, Age, Employees, and Issuing Size. The values for the sample used to analyze one-year post-IPO performance deviate slightly due to a smaller sample size (718 versus 810 IPOs).

Variables	N	Mean	St. Dev.	Min	Max
Pricing Period (weeks)	810	4.6	3.8	3.0	46.0
Filing Period (weeks)	810	15.8	10.4	3.0	53.0
Price Range	810	14.2 %	3.4 %	0.0 %	33.3 %
Age (years)	810	18.9	22.1	1.0	160.0
Employees	810	2,481.6	10,436.2	0.0	153,641.0
Issuing Size (mUSD)	810	195.2	272.3	4.0	2,864.0
Rating	810	1.9	0.9	1	4
Crisis_{short}	810	0.04	0.2	0	1
Price Rev^{Past10}	810	−5.8 %	10.2 %	−113.5 %	17.7 %
R_1^{Past10}	810	12.3 %	8.6 %	−3.2 %	41.5 %
R_1^{Past3M}	810	12.3 %	4.7 %	−2.6 %	22.4 %
$R_{S\&P500}^{Past3M}$	810	3.3 %	4.5 %	−12.6 %	19.5 %

Of the firm-specific variables, Age and Employees are self-explanatory. The variable Issuing Size is defined as the number of shares offered, multiplied by the offer size. Logarithmic values of these variables are used in regressions. The variable Rating refers to the SCOOP rating, predicting the level of expected first-day premium.

Lastly, the remaining variables are considered market-specific variables. The dummy variable Crisis_{short} takes the value 1 if the IPO was completed during the financial crisis in 2008, and 0 otherwise. (When analyzing post-IPO performance, Crisis_{1yr} is employed). The variables Price Rev^{Past10}, R_1^{Past10}, R_1^{Past3M}, and $R_{S\&P500}^{Past3M}$ serve to indicate market conditions at the time of the IPO. The variables Price Rev^{Past10}, R_1^{Past10}, and R_1^{Past3M} can be seen as proxies for whether the IPO market is hot or cold. Positive variable values indicate a hot market. The variable $R_{S\&P500}^{Past3M}$ represents the general market conditions. Positive variable values indicate bullish market conditions.

4 Results

Next, we investigate the relationship between retail investor attention, measured by SVI, and IPO pricing and post-IPO performance. First, the impact of SVI on price revision is studied. Secondly, the relationships of SVI and price revision with underpricing are examined. Thirdly, the impacts of SVI, price revision, and underpricing on IPO performance during the first year of trading are investigated. In addition, different offer-, firm-, and market-specific variables are used as control variables. Table 6 presents an overview of which control variables are employed in the different analyses. For all three analyses, univariate and multivariate regressions are applied. Statistical significance is based on robust standard errors.

Table 6: Control Variables Applied in the Analyses

The table presents an overview of which control variables are applied in the regressions in each of the analyses

Variable	Price Revision	Underpricing	Post-IPO Performance
Pricing Period	○		
Filing Period		○	○
Price Range	○		
Age	○	○	○
Employees	○	○	○
Issuing Size		○	○
Rating		○	○
Crisis_{short}	○		
Crisis_{1yr}			○
Price Rev^{Past10}	○	○	○
$\text{R}_1{}^{Past10}$	○		
$\text{R}_1{}^{Past3M}$		○	○
$\text{R}_{S\&P500}^{Past3M}$	○	○	○

4.1 Price Revision

In this subsection, the relationship between SVI and price revision is examined. Price Rev is used as dependent variable. ASVI, ASVI^{F-P}, and ASVI^{P-O} are used as explanatory variables. Recall that ASVI represents the average ASVI during the whole filing period. ASVI^{F-P} and ASVI^{P-O} represent the average ASVI between the S-1 filing and initial pricing, and between the initial pricing and the IPO date, respectively. In addition, several firm-, offer-, and market-specific characteristics are employed as control variables. The correlations bet-

Table 7: Correlation Matrix - Price Revision

The table shows the correlations between the variables used in the price revision analysis. The variables are defined in Table 1. The sample includes 810 IPOs in the time period from January 2007 through December 2015.

	Price Rev	ASVI	ASVI^{F-P}	ASVI^{P-O}	Pricing Period	Price Range	Age	Employees	Crisis$_{short}$	Price Rev^{Past10}	R$_1^{Past10}$	R$_{S\&P500}^{Past3M}$
Price Rev	1	0.13	0.18	0.10	-0.26	0.01	-0.02	0.20	-0.01	0.08	0.07	0.04
ASVI	0.13	1	0.91	0.72	-0.15	0.01	-0.12	-0.12	-0.03	0.04	0.11	-0.09
ASVI^{F-P}	0.18	0.91	1	0.53	-0.13	0.01	-0.11	-0.07	-0.02	0.06	0.11	-0.10
ASVI^{P-O}	0.10	0.72	0.53	1	-0.26	-0.04	-0.04	-0.07	-0.04	-0.04	0.04	-0.05
Pricing Period	-0.26	-0.15	-0.13	-0.26	1	0.16	-0.13	-0.29	0.04	0.01	0.00	-0.01
Price Range	0.01	0.01	0.01	-0.04	0.16	1	-0.08	-0.16	0.01	0.02	0.00	0.03
Age	-0.02	-0.12	-0.11	-0.04	-0.13	-0.08	1	0.55	0.13	-0.01	0.00	0.10
Employees	0.20	-0.12	-0.07	-0.07	-0.29	-0.16	0.55	1	0.15	-0.01	-0.10	0.01
Crisis$_{short}$	-0.01	-0.03	-0.02	-0.04	0.04	0.01	0.13	0.15	1	0.09	-0.16	-0.02
Price Rev^{Past10}	0.08	0.04	0.06	-0.04	0.01	0.02	-0.01	-0.01	0.09	1	0.30	-0.02
R$_1^{Past10}$	0.07	0.11	0.11	0.04	0.00	0.00	0.00	-0.10	-0.16	0.30	1	0.07
R$_{S\&P500}^{Past3M}$	0.04	-0.09	-0.10	-0.05	-0.01	0.03	0.10	0.01	-0.02	-0.02	0.07	1

ween the variables are shown in Table 7. It can be observed that the correlations between the variables are generally low.

Figure 6 provides a brief understanding of the variables' relationship to price revision on a stand-alone basis. For each independent variable, the set of IPOs is divided on the independent variable's median into two equal-sized subsets. Furthermore, the average price revisions are calculated for the two subsets. Note that the average price revision in the sample is negative. Hence, Figure 6 shows negative values.

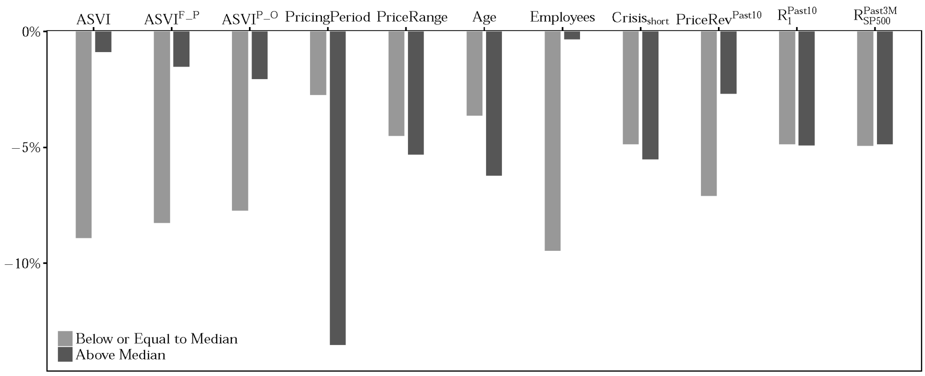


Figure 6: Average Price Revision

The figure plots the average price revisions where, for each independent variable, the set of IPOs is divided on the independent variable's median into two equal-sized subsets. The sample include 810 IPOs in the time period from January 2007 through December 2015.

It is evident from Figure 6 that, on average, lower volumes of Google searches are associated with more negative price revisions than IPOs with higher ASVI. This is also true for both ASVI^{F-P} and ASVI^{P-O}. However, the difference appears to be greater with respect to ASVI^{F-P} than to ASVI^{P-O}. Furthermore, Figure 6 shows a great difference in average price revision for short and long pricing periods. Longer pricing periods have an average price revision that is considerably more negative than shorter pricing periods.

The regressions of price revision with respect to the independent variables are presented in Table 8. Regression 1 shows that, on a stand-alone basis, a positive and highly significant relationship between ASVI and price revision is present. That is, higher Google searches from after the IPO becomes publicly known until the IPO date results in less negative or potentially positive price revisions.

Table 8: Regression Results - Price Revision

The table regresses price revisions on ASVI and offer-, firm-, and market-specific characteristics. The dependent variable is each IPO's price revision during book building. Independent variables are defined in Table 1. The sample includes 810 IPOs in the time period from January 2007 through December 2015. * and ** represents significance at the 5% and 1% level, respectively.

	Dependent variable: Price Revision														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ASVI	0.021**											0.017**			
	(0.007)											(0.007)			
$ASVI^{F-P}$		0.033**											0.027**		0.029**
		(0.007)											(0.007)		(0.008)
$ASVI^{P-O}$			0.008*											0.005	−0.002
			(0.003)											(0.003)	(0.003)
Pricing Period				−0.286**								−0.221**	−0.218**	−0.224**	−0.223**
				(0.038)								(0.041)	(0.039)	(0.041)	(0.041)
Price Range					0.087							0.453	0.439	0.468	0.436
					(0.253)							(0.257)	(0.256)	(0.260)	(0.259)
Age						−0.015						−0.111**	−0.107**	−0.116**	−0.106**
						(0.017)						(0.020)	(0.020)	(0.020)	(0.020)
Employees							0.051**					0.070**	0.069**	0.069**	0.068**
							(0.008)					(0.010)	(0.010)	(0.010)	(0.010)
$Crisis_{short}$								−0.006				−0.009	−0.010	−0.008	−0.010
								(0.045)				(0.033)	(0.033)	(0.034)	(0.033)
Price Rev^{Past10}									0.175			0.139	0.134	0.148	0.131
									(0.098)			(0.119)	(0.122)	(0.101)	(0.117)
R_1^{Past10}										0.175		0.150	0.140	0.171	0.140
										(0.090)		(0.087)	(0.087)	(0.087)	(0.088)
$R_{S\&P500}^{Past3M}$											0.179	0.260	0.279	0.228	0.278
											(0.214)	(0.189)	(0.187)	(0.191)	(0.187)
Constant	−0.073**	−0.076**	−0.067**	0.088**	−0.061	−0.033	−0.177**	−0.049**	−0.039**	−0.070**	−0.055**	−0.100	−0.102	−0.086	−0.096
	(0.010)	(0.009)	(0.010)	(0.020)	(0.034)	(0.022)	(0.024)	(0.009)	(0.010)	(0.014)	(0.011)	(0.056)	(0.054)	(0.057)	(0.057)
Observations	810	810	810	810	810	810	810	810	810	810	810	810	810	810	810
R^2	0.018	0.031	0.009	0.069	0.0002	0.001	0.039	0.00003	0.007	0.005	0.001	0.138	0.147	0.131	0.148

Regression 2 finds a positive relationship between ASVI^{F-P} and price revision on a stand-alone basis. The regression coefficient of 0.033 indicates that an increase by one standard deviation (1.17) in ASVI^{F-P} leads to an absolute change of 3.86% (= 0.033×1.17) in price revision. This result is significant at a 1% level. Thus, a high level of Google searches between S-1 filing and initial pricing tends to lead to less negative and potentially positive revisions during the book building period. Regression 3 finds a positive relationship between ASVI^{P-O} and price revision on a stand-alone basis. The regression coefficient of 0.008 indicates that an increase of one standard deviation (2.72) in ASVI^{P-O} leads to an absolute change of 2.18% (= 0.008×2.72) in price revision. This result is significant at a 5% level.

The relationship between ASVI^{F-P} and price revisions appears to be stronger than the relationship between ASVI^{P-O} and price revisions. This finding is confirmed in Regression 15, which includes both ASVI^{F-P} and ASVI^{P-O}. When combined, ASVI^{P-O} loses all its significance, while ASVI^{F-P} is significant at a 1% level. Thus, we find that Google searches before the initial pricing better predict price revisions than searches during the book building. This indicates that price revision, with respect to retail attention, is a result of not having incorporated the retail investor attention into the indicative price. This observation is in line with findings of Colaco et al. (2014). They find that increased SVI following the S-1 filing positively influences price revision, while increased SVI following initial pricing does not.

Of the control variables, Pricing Period and Employees are found to have reliable relationships with price revision. The negative relationship between pricing period and price revision indicates that longer pricing periods result in more negative price revisions. Employees and price revisions are positively related. This indicates that larger firms tend to experience less negative and potentially positive price revisions. The number of employees is known when the initial price range is set. The relationship between Employees and price revision thereof implies that not all publicly known information at the time of initial pricing is incorporated into the initial price. This is line with the findings of Lowry and Schwert (2001). It is important to note, however, that the predictability of price revision does not represent a profit opportunity, nor is it a cost for the issuing firm.

Altogether, we have three findings regarding price revisions. First, we find a positive relationship between SVI and price revision. Secondly, Google searches before the initial pricing have a substantially stronger impact on price revisions than the searches during book building, which is when the price revision is actually taking place. Hence, it appears as if price revisions, in terms of retail attention, is mostly a result of not having fully incorporated retail investor attention into the initial price. Thirdly, we find that the size of the company, measured by the number of employees, reliably predicts price revisions.

The analysis is replicated using ASVI^{log} - a standardization of ASVI similar to the one employed by Da et al. (2011). Similar results as when using our main standardization are obtained. This indicates that our results are robust with respect to the standardization of ASVI.

4.2 Underpricing

In this subsection, we examine how SVI and price revision is related to underpricing. Underpricing, measured by R_1, is used as dependent variable. ASVI and Price Rev are used as explanatory variables. In addition, several firm-, offer-, and market-specific characteristics are included as control variables.

To allow for an asymmetric, non-linear relationship between underpricing and both ASVI and price revision, we introduce four new variables - two regarding ASVI, and two regarding price revision. The variables are defined as follows:

$$ASVI^{+} = max(ASVI, 0) \ , \qquad ASVI^{-} = min(ASVI, 0)$$
$$PriceRev^{+} = max(PriceRev, 0) \ , \qquad PriceRev^{-} = min(PriceRev, 0).$$

The two ASVI variables enable us to investigate any asymmetry between incorporation of an increase versus a decrease in SVI pre-IPO into the offer price. Regarding price revision, the two new variables enable us to detect any asymmetry between incorporation of positive and negative private information into the offer price.

The correlations between all of the variables are shown in Table 9. Three interesting observations can be pointed out. First, the two variables having the highest correlation with underpricing are Price Rev (0.552) and Rating (0.515). Secondly, for both ASVI and price revision, the positive values have a much higher correlation with underpricing compared to the negative values. This may indicate that they both have an asymmetric relationship with underpricing. Third, the correlations between the independent variables are generally low. The exception is the correlation between Rating and Price Rev. They have a rather high correlation of 0.723.

Figure 7 provides a brief understanding of the variables' relationship with first-day return on a stand-alone basis. For each independent variable, the set

Table 9: Correlation Matrix - Underpricing

The table shows the correlations between the variables used in the underpricing analysis. The variables are defined in Table 1. The sample includes 810 IPOs in the time period from January 2007 through December 2015.

	R_1	ASVI	$ASVI^+$	$ASVI^-$	Price Rev	Price Rev^+	Price Rev^-	Filing Period	Age	Employees	Issuing Size	Rating	$Crisis_{short}$	Price Rev^{Past10}	R_1^{Past3M}	$R_{S\&P500}^{Past3M}$
R_1	1	0.22	0.23	0.03	0.55	0.61	0.36	-0.14	-0.04	0.07	0.10	0.51	-0.06	0.00	0.09	0.04
ASVI	0.22	1	0.99	0.53	0.13	0.17	0.07	-0.39	-0.12	-0.12	0.04	0.18	-0.03	0.04	0.13	-0.09
$ASVI^+$	0.23	0.99	1	0.37	0.13	0.18	0.06	-0.40	-0.11	-0.11	0.04	0.18	-0.05	0.04	0.14	-0.08
$ASVI^-$	0.03	0.53	0.37	1	0.07	0.04	0.07	-0.13	-0.07	-0.09	-0.01	0.10	0.04	0.03	0.02	-0.09
Price Rev	0.55	0.13	0.13	0.07	1	0.79	0.89	-0.10	-0.02	0.20	0.37	0.72	-0.01	0.08	0.05	0.04
Price Rev^+	0.61	0.17	0.18	0.04	0.79	1	0.41	-0.06	-0.08	0.08	0.21	0.58	-0.02	0.06	0.07	0.03
Price Rev^-	0.36	0.07	0.06	0.07	0.89	0.41	1	-0.10	0.02	0.24	0.39	0.64	0.01	0.07	0.03	0.03
Filing Period	-0.14	-0.39	-0.40	-0.13	-0.10	-0.06	-0.10	1	0.09	0.10	0.01	-0.09	0.09	-0.03	-0.18	0.08
Age	-0.04	-0.12	-0.11	-0.07	-0.02	-0.08	0.02	0.09	1	0.55	0.27	0.02	0.13	-0.01	0.01	0.10
Employees	0.07	-0.12	-0.11	-0.09	0.20	0.08	0.24	0.10	0.55	1	0.56	0.19	0.15	-0.01	-0.10	0.01
Issuing Size	0.10	0.04	0.04	-0.01	0.37	0.21	0.39	0.01	0.27	0.56	1	0.31	0.09	0.01	-0.04	-0.02
Rating	0.51	0.18	0.18	0.10	0.72	0.58	0.64	-0.09	0.02	0.19	0.31	1	-0.01	0.07	0.07	0.05
$Crisis_{short}$	-0.06	-0.03	-0.05	0.04	-0.01	-0.02	0.01	0.09	0.13	0.15	0.09	-0.01	1	0.09	-0.24	-0.02
Price Rev^{Past10}	0.00	0.04	0.04	0.03	0.08	0.06	0.07	-0.03	-0.01	-0.01	0.01	0.07	0.09	1	0.18	-0.02
R_1^{Past3M}	0.09	0.13	0.14	0.02	0.05	0.07	0.03	-0.18	0.01	-0.10	-0.04	0.07	-0.24	0.18	1	0.06
$R_{S\&P500}^{Past3M}$	0.04	-0.09	-0.08	-0.09	0.04	0.03	0.03	0.08	0.10	0.01	-0.02	0.05	-0.02	-0.02	0.06	1

of IPOs is divided into two subsets. The average first-day returns are further calculated for each subset. For both ASVI and price revision, the set of IPOs is divided into positive and negative values of ASVI and price revision. Thus, the figure illustrates the average underpricing for the four new variables introduced in the beginning of this section. For each control variable, the set of IPOs is divided on the control variable's median into two equal-sized subsets.

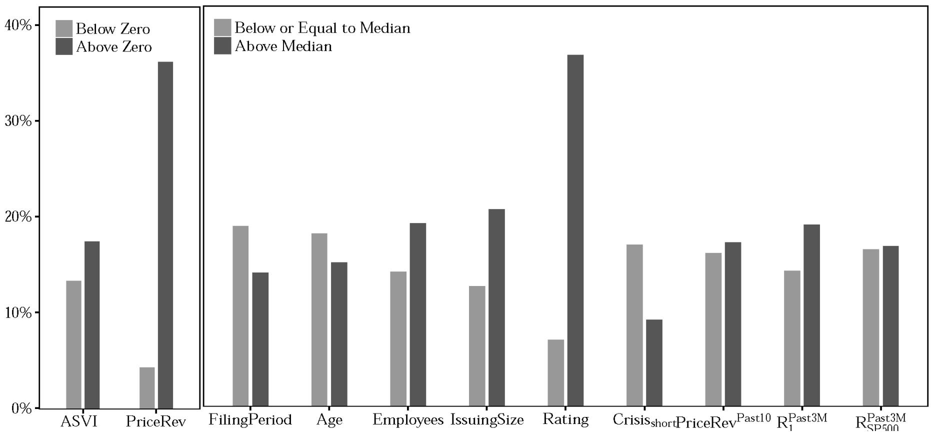


Figure 7: Average First-Day Return

The figure plots the average first-day return where, for each independent variable, the set of IPOs is divided into two subsets. For ASVI and price revision, the set of IPOs is divided on ASVI and price revision respectively with a breakpoint equal to zero. For each control variable, the set of IPOs is divided on the control variable's median into two equal-sized subsets. The sample includes 810 IPOs in the time period from January 2007 through December 2015.

Figure 7 indicates that, on the first day of trading, IPOs with positive ASVI values outperform the companies with negative ASVI values. The average difference is of 4.1%, in absolute terms. Furthermore, IPOs with positive price revisions tend to outperform the IPOs with negative price revisions by 31.9% in absolute terms, on average. Out of the control variables, it can be pointed out that IPOs with high rating appear to be considerably more underpriced than IPOs with a low rating.

The regressions of underpricing with respect to the independent variables are presented in Table 10. Regression 1 indicates that there is a positive and significant linear relationship between ASVI and underpricing. In regression 2, however, ASVI^+ has a positive relationship with underpricing, while ASVI^- has a negative relationship with underpricing. This pattern is also present when controlling for all other variables in regression 15. The magnitude of the coefficients remains approximately the same. Furthermore, both $ASVI^+$ and $ASVI^-$ are significant, with p-values of 0.8% and 1.4% respectively. Thus, IPOs with either a very high increase or decrease in SVI during the filing period tend to be underpriced the most.

To the best of our knowledge, we are currently the only paper that has studied such a non-linear relationship between SVI and underpricing. Da et al. (2011) assume that this relationship is linear. They further conclude that SVI is positively related to underpricing. Note, when we allow for only a linear relationship we get similar results. Da et al. (2011) interpret their findings using the attention theory of Barber and Odean (2008). Within this framework, increased retail attention prior to an IPO can be expected to result in buying pressure from attention-driven investors. This results in higher stock prices in the early aftermarket.

The non-linear relationship found between SVI and underpricing enables us to differentiate between increased and decreased retail attention prior to the IPO. Recall that positive values of ASVI equal an increase in SVI relative to the SVI before filing, while negative values equal a decrease in SVI. Hence, the results for positive ASVI, i.e. increased SVI, are consistent with the attention theory of Barber and Odean (2008). The higher the increase in retail attention in the filing period, the higher the underpricing. However, attention theory does not explicitly state predictions for a decrease in attention. We thus apply other theories to interpret the results for negative ASVI, i.e decreased SVI.

For decreased SVI, our results can instead be seen in light of both Beatty and Ritter (1986) and Ljungqvist et al. (2006). Beatty and Ritter (1986) argue that issuances characterized by greater uncertainty will tend to be more underpriced. This is to compensate investors for learning the true value of these issuances. When an IPO has a decrease in retail investor attention ahead of the IPO, the IPO may appear more precarious. Investors are then compensated for this uncertainty with underpriced stocks. Ljungqvist et al. (2006) argue that underpricing is a compensation for the losses expected from holding stocks, given the risk that the demand in the secondary market will be low. When retail attention ahead of the IPO decreases, it can be reasonable to assume that there is a greater uncertainty about the demand in the aftermarket. Hence, institutional investors take a greater risk when investing in the IPO. Underwriters need to compensate the institutional investors for this risk by offering underpriced stocks. Using the theories of both Beatty and Ritter (1986) and Ljungqvist et al. (2006), it is legitimate why IPOs experiencing a high decrease in retail attention would be more underpriced.

Table 10: Regression Results - Underpricing

The table regresses first-day return on ASVI, Price Rev and offer-, firm-, and market-specific characteristics. The dependent variable is each IPO's first-day return. Independent variables are defined in Table 1. The sample includes 810 IPOs in the time period from January 2007 through December 2015. * and ** represents significance at the 5% and 1% level, respectively.

	Dependent variable: First-day Return														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
ASVI	0.045^{**}													0.029^{**}	
	(0.011)													(0.010)	
ASVI^{+}		0.058^{**}													0.030^{**}
		(0.013)													(0.012)
ASVI^{-}		-0.076													-0.061^{*}
		(0.039)													(0.025)
Price Rev			0.695^{**}											0.385^{**}	
			(0.053)											(0.077)	
Price Rev^{+}				1.370^{**}											1.008^{**}
				(0.205)											(0.221)
Price Rev^{-}				0.244^{**}											0.049
				(0.064)											(0.061)
Filing Period					-0.131^{**}									-0.032	-0.045
					(0.034)									(0.025)	(0.025)
Age						-0.029								-0.005	0.0004
						(0.021)								(0.021)	(0.019)
Employees							0.022^{*}							0.022	0.024
							(0.011)							(0.012)	(0.012)
Issuing Size								0.068^{**}						-0.113^{**}	-0.094^{**}
								(0.023)						(0.024)	(0.023)
Rating									0.159^{**}					0.071^{**}	0.070^{**}
									(0.011)					(0.014)	(0.015)
Crisis_{short}										-0.079^{*}				-0.027	-0.026
										(0.031)				(0.026)	(0.027)
Price Rev^{Past10}											0.010			-0.167	-0.145
											(0.081)			(0.087)	(0.089)
R_1^{Past3M}												0.535^{**}		0.260	0.173
												(0.201)		(0.172)	(0.154)
$\text{R}_{S\&P500}^{Past3M}$													0.241	0.116	0.095
													(0.207)	(0.162)	(0.154)
ASVI x Price Rev														0.100^{**}	0.060^{*}
														(0.034)	(0.028)
Constant	0.115^{**}	0.088^{**}	0.199^{**}	0.108^{**}	0.306^{**}	0.198^{**}	0.109^{**}	-0.383^{*}	-0.133^{**}	0.169^{**}	0.166^{**}	0.100^{**}	0.158^{**}	0.876^{**}	0.651^{**}
	(0.012)	(0.017)	(0.010)	(0.017)	(0.041)	(0.028)	(0.030)	(0.183)	(0.017)	(0.011)	(0.010)	(0.025)	(0.013)	(0.191)	(0.180)
Observations	810	810	810	810	810	810	810	810	810	810	810	810	810	810	810
R^2	0.048	0.059	0.305	0.383	0.019	0.002	0.005	0.010	0.265	0.003	0.00001	0.008	0.002	0.386	0.447

Regression 3 indicates that there is a positive and significant linear relationship between price revision and underpricing. From regression 4, however, it can be seen how this relationship is asymmetric. Both Price Rev^+ and Price Rev^- have positive and significant relationships with underpricing. However, the magnitude of their coefficients differs. The regression coefficient of Price Rev^+ (1.370) indicates that an increase of one percent in price revisions leads to 1.37% higher first-day return. For Price Rev^-, the same increase results in 0.24% higher first-day return. That is, a positive price revision results in higher underpricing than a negative price revision does.

Regression 3 indicates that there is a positive and significant linear relationship between price revision and underpricing. From regression 4, however, it can be seen how this relationship is asymmetric. Both Price Rev^+ and Price Rev^- have positive and significant relationships with underpricing. However, the magnitude of their coefficients differs. The regression coefficient of Price Rev^+ (1.370) indicates that an increase of one percent in price revisions leads to 1.37% higher first-day return. For Price Rev^-, the same increase results in 0.24% higher first-day return. That is, a positive price revision results in higher underpricing than a negative price revision does.

In regression 15, Price Rev^- is no longer significant, while Price Rev^+ continues to be significant at a 1% level. Furthermore, Price Rev^+'s coefficient is approximately three times as large as the coefficient of Price Rev in regression 3 (1.008 versus 0.385, respectively). A linear expression for price revision does thereof not capture the relationship between underpricing and positive price revision to the full extent. Furthermore, as Price Rev^- is not significant, a linear expression would falsely predict first-day return associated with negative price revisions. Hence, there is an asymmetric relationship between underpricing and price revision, as only positive price revision reliably predicts underpricing.

The results indicate that positive price revisions lead to higher underpricing than negative price revisions do. This is in line with the findings of Hanley (1993). It is also in accordance with the partial adjustment theory of Benveniste and Spindt (1989). Benveniste and Spindt (1989) state that positive information revealed by investors leads to positive price revisions. Furthermore, they show that investors must be compensated with underpricing in order to reveal this positive information. Negative information, leading to negative price revisions, does not result in underpricing the same way. Hence, firms that have positive price revisions tend to see a higher underpricing than firms experiencing negative price revisions. That is, positive information is only partially adjusted for.

The interaction variable between ASVI and price revision has a positive coefficient and is significant at a 5% level. Hence, it appears that SVI and price revision affect each others' relationship with underpricing. Figure 8 illustrates the effect of the interaction between ASVI and price revision on underpricing, with all other variables held constant. It can be observed that IPOs with high ASVI and positive price revision seem to be the most underpriced. IPOs with high ASVI but negative price revision, on the other hand, seem to experience the lowest first-day returns.

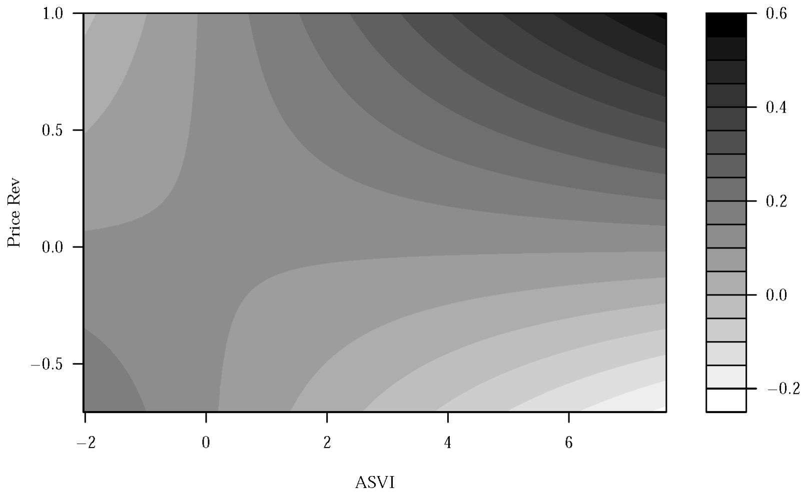


Figure 8: Graphical Illustration of ASVI×Price Rev

The figure shows the change in first-day return as a function of the variation in both ASVI and price revision, with all other variables held constant. That is, it illustrates the variation in R_1 as a function of the interaction variable ASVI×Price Rev from regression 15 in Table 10. The contouring represents the first-day returns. Darker color means higher first-day return.

As far as we know, we are currently the only paper that has studied such an interaction effect between SVI and price revision related to underpricing. Previously papers have studied the predictability of SVI and price revision on underpricing separately. However, as our results indicate that these variables interact, it may be proposed that SVI and price revision need to be seen in relation to each other when predicting first-day return.

Of the control variables, Rating and Issuing Size are the most significant variables, both on a stand-alone basis and in the multivariate regressions. Rating has a positive relationship with underpricing, indicating that high expected first-day premiums tend to result in higher underpricing. Issuing Size has a negative relationship with underpricing. That is, firms with smaller issuing sizes tend to be more underpriced than firms with larger issuing sizes. This may indicate that companies and their investment bankers do not incorporate all publicly available information when setting the offer price. Similar results are found by scholars such as Lowry and Schwert (2001). In addition, note that none of the market variables are reliably related to underpricing in the multivariate regressions. This may suggest that the market conditions are incorporated into the offer price.

The regression model containing all the variables has an R-squared value of 0.45. Compared to other scholars with similar models, such as Da et al. (2011), this is a rather high explanatory power. Hence, our complete regression model is rather well fitted to the data.

To summarize, we have four main findings regarding underpricing. First, we find a non-linear relationship between Google searches prior to the IPO and underpricing. IPOs with either a very high increase or a very high decrease in SVI during the filing period experience the highest level of underpricing. The result for increased SVI is consistent with the attention theory of Barber and Odean (2008). The result for decreased SVI, on the other hand, can be seen in light of IPO theories of both Beatty and Ritter (1986) and Ljungqvist et al. (2006). Secondly, we find an asymmetric relationship between price revision and underpricing. Offer prices appear to be better adjusted to negative information than positive information. This is in line with the partial adjustment theory of Benveniste and Spindt (1989). Thirdly, SVI and price revision appear to affect each others' relationship with underpricing. IPOs with both high SVI and positive price revision tend to be the most underpriced. Fourth, both rating and issuing size are predictably related to underpricing. This indicates that not all publicly available information is incorporated into offer prices.

The analysis is replicated using ASVI^{log} - a standardization of ASVI similar to the one employed by Da et al. (2011). Similar results as when using our main standardization are obtained. This indicates that our results are robust with respect to the standardization of ASVI.

4.3 Post-IPO Performance

In this subsection, we investigate how SVI, price revision, and underpricing are related to post-IPO performance up until one year. Excess market return is used as dependent variable. ASVI, Price Rev, and R_1 are used as explanatory variables. In addition, several firm-, offer-, and market-specific characteristics are employed as control variables.

We start by analyzing the relationships between the independent variables and one-year post-IPO performance. Secondly, we investigate how the same relationships evolve throughout the first year of trading, i.e. for trading days 2 through 252.

One-Year Post-IPO Performance

One-year excess market return, R_{252}^{ExMkt}, is used as the dependent variable when analysing the one-year post-IPO performance. When graphing this variable against R_1, a pattern resembling a quadratic relationship can be observed. We therefore introduce a quadratic transformation for the variable R_1:

$$R_1^{Extrm} = (R_1 - \bar{R_1})^2$$

This variable allows us to interpret how values of R_1 deviating from the mean affect the IPO's performance during the first year of listing.

The correlations between R_{252}^{ExMkt} and the other variables are shown in Table 11. The correlations are generally low. Note also that all the variables, except for Age, are negatively correlated with R_{252}^{ExMkt}.

Figure 9 provides a brief understanding of the variables' relationship to one-year post-IPO performance on a stand-alone basis. For each independent variable, the set of IPOs is divided on the independent variable's median into two equal-sized subsets. The average excess market returns are then calculated for each subset. For ASVI and first-day return, the difference between the average one-year excess market return for IPOs with high and low values is not very substantial. However, for price revision, rating and underpricing the past three months, R_1^{Past3M}, the difference is quite sizable. For all three variables, IPOs with values below the median appear to considerably outperform IPOs with values above the median. Hence, IPOs with positive price revisions, a high rating or that take place in hot IPO markets appear to underperform on a one-year perspective.

When including the quadratic variable for first-day return, we are able to capture a non-linear relationship between R_1 and R_{252}^{ExMkt}. To get a brief understanding of this relationship, we plot the average excess market return when dividing the set of IPOs by extreme and moderate first-day returns. That is, the sample is divided into two subsets; (1) IPOs with R_1 values in the upper and lower quartiles, and (2) IPOs with R_1 values in the middle range. This is

Table 11: Correlation Matrix - One-Year Post-IPO Performance

The table shows the correlations between the variables used in the one-year post-IPO performance analysis. The variables are defined in Table 1. The sample includes 718 IPOs in the time period from January 2007 through February 2015.

	R_{252}^{ExMkt}	ASVI	Price Rev	R_1	R_1^{Extrm}	Filing Period	Age	Employees	Issuing Size	Rating	$Crisis_{1yr}$	Price Rev^{Past10}	R_1^{Past3M}	$R_{S\&P500}^{Past3M}$
R_{252}^{ExMkt}	1	-0.01	-0.12	-0.07	-0.10	-0.03	0.04	-0.01	-0.01	-0.14	-0.05	-0.12	-0.10	-0.11
ASVI	-0.01	1	0.15	0.17	0.13	-0.39	-0.11	-0.07	0.07	0.18	-0.20	-0.01	0.13	-0.06
Price Rev	-0.12	0.15	1	0.56	0.30	-0.10	-0.04	0.18	0.36	0.72	0.04	0.09	0.04	0.03
R_1	-0.07	0.17	0.56	1	0.69	-0.12	-0.03	0.09	0.09	0.52	-0.03	-0.02	0.09	0.04
R_1^{Extrm}	-0.10	0.13	0.30	0.69	1	-0.13	-0.05	0.01	0.00	0.23	-0.05	-0.05	0.08	0.00
Filing Period	-0.03	-0.39	-0.10	-0.12	-0.13	1	0.07	0.09	0.00	-0.07	0.22	0.01	-0.17	0.04
Age	0.04	-0.11	-0.04	-0.03	-0.05	0.07	1	0.56	0.26	0.02	-0.01	-0.03	0.00	0.09
Employees	-0.01	-0.07	0.18	0.09	0.01	0.09	0.56	1	0.55	0.18	0.06	-0.03	-0.11	0.01
Issuing Size	-0.01	0.07	0.36	0.09	0.001	0.00	0.26	0.55	1	0.30	0.02	0.01	-0.05	-0.03
Rating	-0.14	0.18	0.72	0.52	0.23	-0.07	0.02	0.18	0.30	1	0.03	0.09	0.06	0.06
$Crisis_{1yr}$	-0.05	-0.20	0.04	-0.03	-0.05	0.22	-0.01	0.06	0.02	0.03	1	0.20	-0.15	-0.13
Price Rev^{Past10}	-0.12	-0.01	0.09	-0.02	-0.05	0.01	-0.03	-0.03	0.01	0.09	0.20	1	0.19	-0.01
R_1^{Past3M}	-0.10	0.13	0.04	0.09	0.08	-0.17	0.00	-0.11	-0.05	0.06	-0.15	0.19	1	0.10
$R_{S\&P500}^{Past3M}$	-0.11	-0.06	0.03	0.04	0.00	0.04	0.09	0.01	-0.03	0.06	-0.13	-0.01	0.10	1

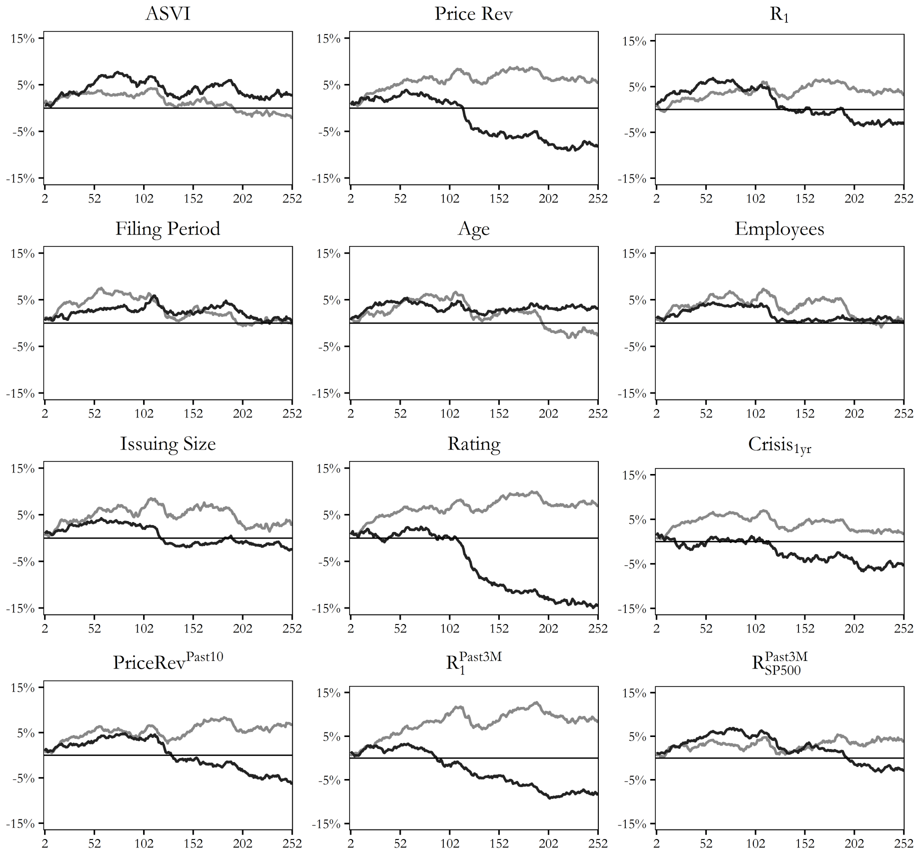


Figure 9: Average Excess Market Return

The figure plots the average excess market return from trading day 2 through 252. For each independent variable, the set of IPOs is divided on the independent variable's median into two equal-sized subsets. The light grey line represents the subset of IPOs with an independent variable value below or equal to the median. The dark grey line represents the subset of IPOs with an independent variable value above the median. The sample includes 718 IPOs in the time period from January 2007 through February 2015

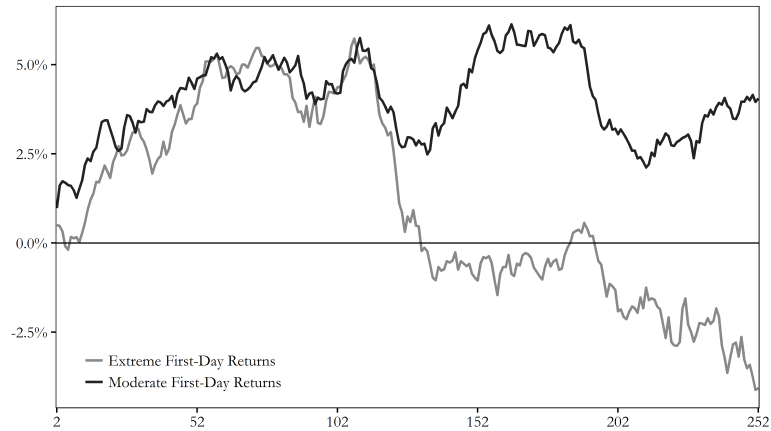


Figure 10: Average Excess Market Return - Moderate and Extreme R_1

The figure plots the average excess market return from trading day 2 through 252. The set of IPOs is divided into two subsets: (1) IPOs with R_1 values in the upper and lower quartiles, and (2) IPOs with R_1 values in the middle range. The dark grey line represents IPOs with R_1 in the upper and lower quartiles. The light grey line represents IPOs with moderate values of R_1. The sample includes 718 IPOs in the time period from January 2007 through February 2015

presented in Figure 10. This is presented in Figure 10. Evidently, the average excess market returns of the two samples follow each other very closely during the first six months, until the end of the lock-up period. From there on, the IPOs with extreme first-day returns underperform considerably towards the end of the first year.

Table 12 presents the regression results for one-year excess market return with respect to the independent variables. Regression 1 and regressions 15-17 show no significant relationship between ASVI and R_{252}^{ExMkt} - neither on a stand-alone, nor multivariate basis. In regression 2 we find a negative and significant relationship between price revision and R_{252}^{ExMkt}. This implies that adjustments of the IPO offer price in the positive direction have a negative effect on the one-year excess market return. However, in the multivariate regressions, price revision no longer has a significant relationship with R_{252}^{ExMkt}. This indicates that there are other variables than price revision that better predict the IPO's performance after one year.

Rating is the most significant independent variable, both on a stand-alone basis and in the multivariate case. We find that IPOs with high ratings tend to have lower one-year excess market returns. Thus, IPOs that are expected to have a high first-day premium appear to perform worse on a one-year perspective.

Table 12: Regression Results - One-Year Post-IPO Performance

The table regresses one-year excess market returns on ASVI, Price Rev, R_1 and offer-, firm-, and market-specific characteristics. The dependent variable is the individual IPO's cumulative return one year after the IPO adjusted by the market return during the same period. The S&P 500 index is used as a proxy for the market return. The variables are defined in Table 1. The sample includes 718 IPOs in the time period from January 2007 through February 2015. * and ** represents significance at the 5% and 1% level, respectively.

	Dependent variable: One-Year Excess Market Return																
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
ASVI	−0.002														−0.001	0.002	−0.0004
	(0.018)														(0.018)	(0.018)	(0.018)
Price Rev		-0.319^{**}													−0.084	−0.003	−0.096
		(0.124)													(0.172)	(0.161)	(0.173)
R_1			−0.167		−0.014										0.025		0.291
			(0.093)		(0.139)										(0.117)		(0.157)
R_1^{Extrm}				-0.311^{**}	-0.298^{*}											-0.244^{**}	-0.457^{**}
				(0.092)	(0.147)											(0.077)	(0.145)
Filing Period						−0.068									−0.095	−0.107	−0.108
						(0.082)									(0.076)	(0.076)	(0.076)
Age							0.066								0.114	0.110	0.111
							(0.053)								(0.061)	(0.061)	(0.060)
Employees								−0.006							−0.037	−0.033	−0.039
								(0.028)							(0.036)	(0.036)	(0.036)
Issuing Size									−0.011						0.064	0.043	0.064
									(0.053)						(0.067)	(0.066)	(0.066)
Rating										-0.099^{**}					-0.080^{**}	-0.076^{**}	-0.096^{**}
										(0.026)					(0.028)	(0.029)	(0.029)
$Crisis_{1yr}$											−0.069				−0.059	−0.061	−0.060
											(0.059)				(0.053)	(0.053)	(0.053)
Price Rev^{Past10}												-0.948^{*}			−0.669	-0.729^{*}	−0.692
												(0.387)			(0.364)	(0.357)	(0.360)
R_1^{Past3M}													-1.290^{**}		-1.083^{*}	-1.013^{*}	-1.054^{*}
													(0.458)		(0.453)	(0.442)	(0.445)
$R_{S\&P500}^{Past3M}$														-1.498^{*}	-1.419^{*}	-1.433^{*}	-1.462^{*}
														(0.584)	(0.590)	(0.592)	(0.598)
Constant	0.005	−0.013	0.029	0.024	0.026	0.077	−0.070	0.018	0.091	0.187^{**}	0.018	−0.046	0.160^{*}	0.057	−0.138	0.040	−0.107
	(0.032)	(0.022)	(0.033)	(0.031)	(0.034)	(0.098)	(0.077)	(0.088)	(0.441)	(0.063)	(0.036)	(0.028)	(0.063)	(0.037)	(0.533)	(0.520)	(0.517)
Observations	718	718	718	718	718	718	718	718	718	718	718	718	718	718	718	718	718
R^2	0.00003	0.014	0.005	0.011	0.011	0.001	0.002	0.0001	0.0001	0.021	0.002	0.015	0.011	0.013	0.058	0.064	0.070

The fact that we do not find a significant relationship between SVI and one-year performance differs from the findings of Da et al. (2011). For their sample of IPOs, they conclude that pre-IPO Google searches predict post-IPO underperformance. Da et al. (2011) interpret their findings using the attention theory of Barber and Odean (2008). Within this framework, attention-based purchases by many investors temporarily inflate a stock's price, leading to disappointing subsequent returns.

To the extent that SVI is a direct measure of retail attention, our results for post-IPO performance are not in line with this subsequent price reversal following high attention. Our results are instead similar to those of Liu, Sherman, and Zhang (2009). Measuring investor attention by media coverage, Liu et al. (2009) find that increased pre-IPO investor attention does not lead to neither price reversal, nor underperformance during the first year of trading.

When interpreting SVI's predictability for IPO returns, Da et al. (2011) also consider the so-called anticipation hypothesis. They recognize the possibility that Google searches may be driven by market participants' expectations of initial returns. They state that if investors expect a high first-day return the search level prior to the IPO is higher, opposed to if the first-day return is expected to be low. In this case, the expectation of higher first-day returns cause higher SVI (i.e., the "anticipation hypothesis"), not the other way around (i.e., the "attention hypothesis").

Da et al. (2011) investigate the anticipation hypothesis using SCOOP Rating as a proxy for the expected first-day return. They conclude that the attention hypothesis is more consistent with their results, due to two reasons. First, when controlling for Rating, i.e. the expected first-day return, the relationship between SVI and underpricing is unaffected. Secondly, the anticipation hypothesis cannot explain SVI's predictability for post-IPO return reversal.

Our results appear to be more in line with the anticipation hypothesis than the attention hypothesis. First, the relationship obtained between SVI and underpricing changes with respect to whether the SCOOP Rating is controlled for or not. When rerunning the regressions in Table 12 both with and without Rating, we find that the linear representation of SVI becomes less significant when Rating is included. If expected first day premium drives the frequency of SVI, this change in significance is what one would expect. The non-linear representation of SVI, however, becomes more significant when Rating is included. This indicates that the SVI not driven by expectations in first-day premium has a relationship with underpricing that is better captured by a non-linear representation of SVI than a linear representation. Secondly, for post-IPO performance, we find that Rating reliably predicts underperformance while SVI does not. That is, we find that the expected first-day premium predicts high first-day return and post-IPO reversal, while SVI does not. Hence, the anticipation hypothesis is overall more consistent with our results than the attention hypothesis is.

Moreover, the subsequent price reversal following attention-based purchases is based on the assumption that the investor attention dissipates in time. In our data sample, the average Google search frequency post-IPO stabilizes at a higher level than before the IPO. Hence, the firms in our sample seem to maintain a certain level of retail investor attention after going public. In the data sample of Da et al. (2011), however, the average SVI returns to its pre-IPO level after the IPO. Hence, the behavior of their data is more in line with the attention pattern proposed by Barber and Odean (2008). This is a possible reason for the difference in the results of Da et al. (2011) and ourselves. Hence, it may be advised that future research not only considers the level of Google searches prior to the IPO, but also post-IPO SVI, when investigating price reversal.

Regressions 3 through 5 represent the relationship between first-day return and one-year excess market return on a stand-alone basis. We find that the linear expression of R_1 is not significant, while the quadratic representation of R_1 is significant at a 1% level. This finding is also present when controlling for other variables in regressions 15-17. The results imply that IPOs that experience close to average first-day returns (16.5% for our dataset) perform better after one year, compared to IPOs where first-day returns deviate largely from the mean. This indicates that some degree of underpricing is favorable for the post-IPO performance. IPOs with extreme values of first-day return, on the other hand, tend to have lower one-year returns.

The relationship between underpricing and post-IPO performance is substantially researched in IPO literature. However, there is no consensus among scholars. J. R. Ritter (1991) documents that underpricing and long-run performance are negatively, but weakly related, whereas Krigman et al. (1999) find that IPOs with positive, but moderate, first-day return outperform other IPOs during the first year. Da et al. (2011) find no significant relationship between underpricing and one-year post-IPO performance. These scholars, however, investigate this as a linear relationship. When we allow for only a linear relationship, we get results similar to those of Da et al. (2011).

The two market-specific variables R_1^{Past3M} and $R_{S\&P500}^{Past3M}$ have significant and negative relationships with R_{252}^{ExMkt}, both in the univariate and in the multivariate regressions. This indicates that IPOs happening during hot or bull markets tend to see a lower one-year excess market return. Out of the two variables, past market return, $R_{S\&P500}^{Past3M}$, is the most significant in economic terms. Its regression coefficient of -1.462, in regression 17, indicates that an increase of one standard deviation (0.045) leads to -6.58% (= $-1.462 \times 4.5\%$) lower one-year excess market return. Similar interpretations for past average underpricing, R_1^{Past3M}, can be made. Here, an increase of one standard deviation will lead to a change in one-year performance of -4.95%.

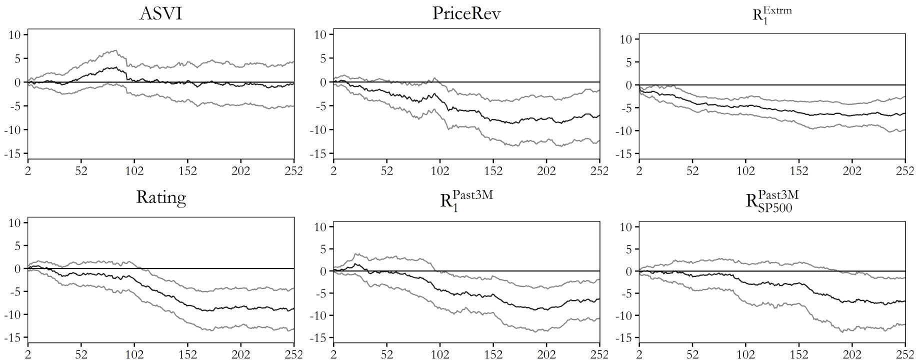
The negative relationship between market conditions at the time of the IPO and post-IPO performance is supported by J. R. Ritter (1991) and Schultz (2003). They find that IPOs happening during hot markets perform worse post-IPO than companies going public during colder periods. Furthermore, Ibbotson et al. (1994) argue that there exists an optimistic sentiment among investors during hot markets, causing excessive underpricing. They argue that in the long-run, the IPO stock prices will revert back to more realistic values. This results in IPO underperformance.

Long-run performance may be the most controversial area of IPO research. The results are sensitive not only to methodology, but also to the exact time period and data sample chosen (J. Ritter & Welch, 2002). Our analyses are based on different IPO samples and include different control variables, compared to Da et al. (2011) and other scholars. This may be a reason for the difference in our results.

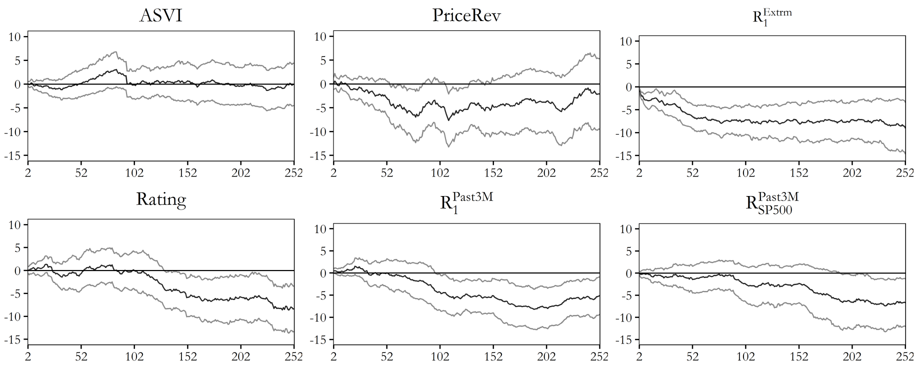
To summarize, we have four main findings regarding the post-IPO performance. First, we find no relationship between one-year excess market return and neither Google searches during the filing period, nor price revision. The lack of relationship between SVI and post-IPO performance is inconsistent with the attention theory explanation. Secondly, we find a negative relationship between expected first-day premium and one-year excess market return. Hence, our results are more in line with the anticipation hypothesis than the attention hypothesis. Thirdly, IPOs that experience close to average first-day returns perform better after one year compared to IPOs with first-day returns deviating largely from the mean. This implies that moderate underpricing is favourable. Fourth, we find that IPOs happening during bullish or hot market conditions are the worst performers on a one-year perspective.

Iterative Regressions

We also examine how the relationships between the independent variables and the post-IPO excess market return evolve over time. Figure 11 illustrates the evolution of the regression coefficients when the dependent variable, the excess market return, varies in time from trading day, t, 2 through 252. The coefficients



(a)



(b)

Figure 11: Iterative Stand-Alone and Multivariate Regressions

Figure (a) illustrates the stand-alone regressions for excess market return from trading days 2 through 252 with respect to independent variables. Only the independent variables we find the most interesting are represented in the figure. Figure (b) shows the same variables as Figure (a), but when applied in the multivariate regression similar to regression 17 in Table 12 with respect to the included independent variables. The dark line represents the evolution of the regression coefficients when the dependent variable varies in time. The coefficients are shown in percentage. They represent the change in excess market return when the independent variable changes by one standard deviation, all other variables held constant. The light grey lines represent the 95% robust confidence intervals of the respective variable. Hence, when zero is not within the interval the coefficient is considered significant at a 5% level.

are shown in percentage. They represent the change in excess market return when the independent variable changes by one standard deviation, all other variables held constant. The lighter grey lines represent the 95% robust confidence intervals of the respective variable. Hence, when zero is not within the interval, the null-hypothesis can be rejected and the coefficient is considered significant at a 5% level. Figure 11a shows the independent variables that have the most interesting results on a stand-alone basis. Figure 11b shows the results for the same variables in the multivariate case. The multivariate regression is equivalent to regression 17 in Table 12 in terms of included variables.

From Figure 11, we find that neither Google searches nor price revision are reliably related to excess market return throughout the first year of listing. Rating, however, has a negative relationship with excess market returns after approximately six months. Furthermore, the highly significant, non-linear relationship between first-day return and one-year post-IPO excess market return is present throughout almost the entire first year. The relationship has a steady decrease in magnitude throughout the whole period. Thus, the difference between the performance of IPOs with extreme versus moderate first-day returns increases with time. Furthermore, past average underpricing has a negative and significant relationship with R_t^{ExMkt} from around six months. Past market return, on the other hand, is only significant towards the end of the period.

The most pronounced relationships in Table 12 are also significant throughout large periods during the first year of trading. This supports and gives credibility to our results; they are not obtained by chance on trading day 252. By investigating the observed relationships throughout the first year of trading, our research also distinguishes itself from Da et al. (2011)'s.

As previously, the analyses for post-IPO performance are replicated using ASVI^{log} - a standardization of ASVI similar to the one employed by Da et al. (2011). Similar results as when using our main standardization are obtained. This indicates that our results are robust with respect to the standardization of ASVI. The analyses are also replicated using excess benchmark portfolio return, R_t^{ExBM}, instead of excess market return, R_t^{ExMkt}, as the dependent variable. Similar results are obtained. Hence, the analysis is robust for adjustments of raw IPO returns.

5 Conclusion

This paper investigates the impact on retail investor attention, measured by SVI, on price revision, underpricing, and post-IPO performance. We also examine how the three IPO phenomena are related to each other.

We find that Google searches prior to an IPO are positively related to price revision. However, the Google searches before the initial pricing have a stronger relationship with price revision than searches during book building. This indicates that price revision, with respect to retail attention, is mostly a result of not having fully incorporated retail investor attention into the initial price.

Furthermore, we find that IPOs with either very high increase or decrease in Google searches in the filing period experience the highest level of underpricing. The result for increased retail attention is consistent with the attention theory of Barber and Odean (2008) - the higher the increase in retail investor attention, the higher underpricing. The result for decreased retail attention, on the other hand, can be seen in light of both Beatty and Ritter (1986) and Ljungqvist et al. (2006), who claim that IPOs characterized by greater uncertainty or higher risk are underpriced to compensate institutional investors. Moreover, we find that positive price revisions result in higher underpricing, compared to negative price revisions. This is in accordance with the partial adjustment theory of Benveniste and Spindt (1989). In addition, SVI and price revision seem to affect each others' relationship with underpricing. We find that IPOs with both high SVI and positive price revisions tend to be underpriced the most. Hence, we suggest that SVI and price revision should be seen in relation to each other when predicting underpricing.

We find no relationship between SVI and one-year post-IPO performance. If SVI's relationship with underpricing was due to retail investor buying stock that had received more attention, we would expect the stock price to eventually revert, leading to a negative relation between SVI and post-IPO performance. Thus, the lack of relationship between SVI and post-IPO performance is inconsistent with the attention theory. Instead, we find that SCOOP Rating, representing expected first-day premium, predicts both high first-day return and post-IPO underperformance. Hence, our results are more in line with the anticipation hypothesis than the attention hypothesis. That is, it may seem like SVI is driven by expectations of high first-day returns. Furthermore, we find that IPOs experiencing close to average first-day return perform better after one year, compared to IPOs where first-day returns deviate largely from the mean.

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A Appendix

A.1 Companies in Final IPO Dataset (810 Companies)

A
A10 Networks
AAC
Acceleron Pharma
Accretive Health
Accuray
AcelRx Pharmaceuticals
Achaogen
Aclaris Therapeutics
Adamas Pharmaceuticals
Addus HomeCare
Adecoagro
Adesto Technologies
ADMA Biologics
Aduro Biotech
Advanced Drainage Systems
AECOM Technology
Aegerion Pharmaceuticals
Aerie Pharmaceuticals
Aeroflex
Aerohive Networks
AeroVironment
Affimed Therapeutics
Agile Therapeutics
Agios Pharmaceuticals
Air Lease
Airvana
Akebia Therapeutics
Alarm.com
Alcobra
Alder BioPharmaceuticals
Alimera Sciences
Alpha and Omega Semiconductor
Amber Road
Ambit Biosciences
AMC Entertainment
Amedica
Ameresco
American Public Education
American Water Works
Amicus Therapeutics
Amphastar Pharmaceuticals
Amyris
Anacor Pharmaceuticals
Ancestry.com
Angie's List
Animal Health International
Annie's
Antero Midstream
Antero Resources
Apigee
AppFolio
Applied Genetic Technologies
Applied Optoelectronics
Approach Resources
Aquinox Pharmaceuticals
Aratana Therapeutics
Arcadia Biosciences
Arcos Dorados
ArcSight
Ardelyx
Ardmore Shipping
Argos Therapeutics
Arista Networks
Aruba Networks
ARYx Therapeutics
Aspen Aerogels
Atara Biotherapeutics
Atento
athenahealth
Athlon Energy
Atlassian
Atossa Genetics
aTYR PHARMA
Audience
Auris Medical
Auspex Pharmaceuticals
AuthenTec
Avago Technologies
Avalanche Biotechnologies
Avenue Financial
AVEO Pharmaceuticals
AVG Technologies
Avinger
Avolon
Axalta Coating Systems
Axsome Therapeutics

B
Baltic Trading
Bankrate
BankUnited
Barracuda Networks
Bazaarvoice
Bellicum Pharmaceuticals
Benefitfocus
Berry Plastics
BigBand Networks
BIND Therapeutics
Biocept
Biodel
BioForm Medical
BioFuel Energy
Black Knight Financial Services
Blackhawk Network
BladeLogic
Blue Buffalo Pet Products
bluebird bio
Blueprint Medicines
Body Central
Boingo Wireless
Boise Cascade
Bojangles
Bonanza Creek Energy
Boot Barn
Booz Allen Hamilton
Borderfree
Box
Box Ships
Bravo Brio Restaurant
Bridgepoint Education
Bright Horizons Family Solutions
Brightcove
BroadSoft
Burlington
BWAY

C
CJ Energy Services
C1 Financial
Caesars Entertainment
CafePress
CAI International
Calithera
Calix Networks
Cara Therapeutics
Carbonite
CardioNet
CardTronics
Care.com
Cascal
CastlePoint
Castlight Health
Catabasis Pharmaceuticals
Catalent
Cavium Networks
CBOE
CDW
Celladon
Cellu Tissue
Cellular Dynamics International
Cempra
Century Communities
Ceres
Cerulean Pharma
ChannelAdvisor
CHC
Chefs Warehouse
Chegg
ChemoCentryx
Chiasma
Chimerix
China Commercial Credit
China Digital TV
Chuy's
Cinemark
Civitas Solutions
Clean Energy Fuels
Clearwire
Clovis Oncology
ClubCorp
CM Finance
Cnova
Cobalt International Energy
Codexis
Coherus BioSciences
Collegium Pharmaceutical
CoLucid Pharmaceuticals
CommScope
Compellent
Complete Genomics
comScore
Comverge
Conatus Pharmaceuticals
Concert Pharmaceuticals

Concho Resources
ConforMIS
Conifer
ConnectOne
Connecture
Constant Contact
Container Store
Continental Building Products
Control4
Convio
Corium International
Cornerstone OnDemand
Costamare
Coty
COUPONS.com
Covisint
CPI Card
Crude Carriers
Cvent
Cyan
CyberArk Software
CytomX Therapeutics

D
Data Domain
Dave Buster's Entertainment
DAVIDsTEA
Delphi Automotive
Deltek
Demand Media
DemandTec
Demandware
Dermira
Diamond Resorts International
Diamondback Energy
Dice
Dicerna Pharmaceuticals
Digital Domain Media
Diplomat Pharmacy
Dole Foods
Dollar General
Douglas Dynamics
Duff Phelps
Duluth
Dunkin Brands
Durata Therapeutics
DynaVox

E
E2open
Eagle Pharmaceuticals
Eclipse Resources
Edge Therapeutics
Edgen
Egalet
El Pollo Loco
Eleven Biotherapeutics
Ellie Mae
Eloqua
Emdeon
Employers
Enanta Pharmaceuticals
EndoChoice
Endocyte
Endurance International
Energy Recovery
EnerNOC
Enphase Energy
Entellus Medical
EnteroMedics
Entropic Communications
Envestnet
Enzymotec
EP Energy
EPAM Systems
Epizyme
Epocrates
Equity Bancshares
Esperion Therapeutics
Essent
Etsy
Eurand
EVERTEC
Everyday Health
Evoke Pharma
Evolent Health
Exa
ExactTarget
ExamWorks
Express
Eyegate Pharmaceuticals

F
Fabrinet
Fairway
Fate Therapeutics
FCStone
Fenix Parts
FGX International
FibroGen
Fidelity Guaranty Life
Fifth Street Asset Management
Financial Engines
FireEye
First Data
First Interstate BancSystem
First NBC Bank
First Republic Bank
Fitbit
Five Below
Five Prime Therapeutics
Five9
Flagstone Reinsurance
FleetCor Technologies
FleetMatics
Flex Pharma
Flexion Therapeutics
Fluidigm
FMSA
Foamix
Fogo de Chão
Fortegra Financial
Fortinet
Fortress Investment
Forum Energy Technologies
Foundation Medicine
Fox Factory
Francescas
Franks International
Freshpet
Fusion-io
FX Alliance
FXCM

G
GAIN Capital
GasLog
Generac
Genocea Biosciences
Genoptix
Genpact
Gevo
Gigamon
Glaukos
Global Blood Therapeutics
Global Defense National Security Systems
Global Defense Technology Systems
Global Geophysical Services
GlobeImmune
Glu Mobile
GlycoMimetics
GNC
GoDaddy
GoPro
Gordmans Stores
Graham Packaging
Great Western
Green
Green Dot
Greenway Medical Technologies
Groupon
Grubhub
GSE
GSI Technology
Guidewire Software

H
Habit Restaurants
HD Supply
Health Insurance Innovations
HealthEquity
Heat Biologics
Helicos BioSciences
Heritage Insurance
HFF
hhgregg
Higher One
Hilton Worldwide
HireRight
Histogenics
HomeAway
Horizon Pharma
Horsehead
Hortonworks
Houghton Mifflin Harcourt
Houlihan Lokey
HTG Molecular Diagnostics
HubSpot
Hyatt Hotels
Hyde Park
Hyperion Therapeutics

I
ICx Technologies
Ignite Restaurant
Immune Design
Imperial
Imperva
Imprivata
IMS Health
INC Research
Independence Contract Drilling
Independent Bank
Infinera
Infoblox
Inogen
Inotek Pharmaceuticals

Inovalon
Inphi
Installed Building Products
Instructure
Insulet
Intellon
Intelsat
Intercept Pharmaceuticals
Intermolecular
Internet Brands
Intersect ENT
InterXion
Intralink
Intrawest Resorts
Intrexon
InvenSense
Investar
Invitae
Invuity
IPC The Hospitalist Company
iRadimed

J
Jaguar Animal Health
James River
Jazz Pharmaceuticals
JGWPT
Jive Software
JMP
Jones Energy
Juno Therapeutics

K
K12
K2M
KaloBios Pharmaceuticals
KAR
Karyopharm Therapeutics
KemPharm
Kinder Morgan
KiOR
Kips Bay Medical
Kite Pharma
Kornit Digital
Kosmos Energy
KYTHERA Biopharmaceuticals

L
La Quinta
Ladder Capital
Laredo Petroleum
LDR
LendingClub
LGI Homes
LifeLock
Limelight Networks
LinkedIn
Linn Co
Liquid
Loxo Oncology
LPL Financial
lululemon athletica
Lumber Liquidators
Lumenis
Luxoft

M
M/A-COM Technology Solutions
Macrocure
MacroGenics
MakeMyTrip
MAKO Surgical
Malibu Boats
Manchester United
Manning Napier
MAP Pharmaceuticals
Marcus Millichap
Marin Software
Marinus Pharmaceuticals
Marketo
Markit
Marrone Bio Innovations
Masimo
Matador Resources
Match
Mattress Firm
Mavenir Systems
MaxLinear
MaxPoint Interactive
MCBC
Mead Johnson Nutrition
MedAssets
Medical Transcription Billing
Medidata Solutions
MediWound
Medley Management
MedWorth
Mellanox Technologies
Memorial Resource Development
MEMSIC
MercadoLibre
Merrimack Pharmaceuticals
Meru Networks
Metaldyne
MetroPCS Communications
Michael Kors
Midstates Petroleum
Milacron
Millennial Media
Mimecast
MINDBODY
Mirna Therapeutics
Mitel Networks
Mobile Iron
Mobileye
Model N
Moelis
Molycorp
Monotype Imaging
Montage Technology
Motricity
MRC Global
MSCI
MyoKardia

N
Nanosphere
NanoString Technologies
Natera
National Bank
National CineMedia
National Commerce
Nationstar Mortgage
Natural Grocers by Vitamin Cottage
Navigator
Neff
NeoPhotonics
Neos Therapeutics
NephroGenex
Netezza
NetSpend
NetSuite
NeuroDerm
NeurogesX
Neutral Tandem
Nevro
New Relic
NewLink Genetics
Nimble Storage
NMI
Noodles Company
Norcraft Companies
Nord Anglia Education
NovoCure
NuPathe
NXP Semiconductors

O
Oasis Petroleum
Ocular Therapeutix
Oculus Innovative Sciences
Ollie's Bargain Outlet
OM Asset Management
Omthera Pharmaceuticals
On Deck Capital
OncoMed Pharmaceuticals
Onconova Therapeutics
Ooma
OpenTable
OpGen
Ophthotech
Opnext
Opower
Optimer Pharmaceuticals
Opus Bank
Orbitz Worldwide
Orexigen Therapeutics
Orion Energy Systems
Orion Engineered Carbons
Otonomy

P
Pacira Pharmaceuticals
Pandora Media
Palo Alto Networks
Papa Murphy's
Paragon Shipping
Parnell Pharmaceuticals
Parsley Energy
Patriot National
Pattern Energy
Paycom Software
Paylocity
Peak Resorts
Penumbra
Performant Financial
Pfenex
PGA
Pharmasset
Phibro Animal Health
Pinnacle Foods
Pinnacle Gas Resources
Planet Fitness
Polypore International
Portola Pharmaceuticals
Potbelly
Power Medical Interventions
Premier
Presbia
Primaerica
Primo Water

Professional Diversity Network
ProNAi Therapeutics
Proofpoint
PROS
Prosensa
Proteon Therapeutics
Proto Labs
PTC Therapeutics
Pure Storage
Pzena Investment Management

Q
Q2
Qualys
QuinStreet
Quintiles Transnational

R
Rackspace Hosting
Radius Health
Rally Software Development
Rapid7
RCS Capital
ReachLocal
Real Goods Solar
RealD
Realogy
RealPage
Receptos
REGENXBIO
Regional Management
Relypsa
REMAX
Renewable Energy
Response Genetics
Responsys
RetailMeNot
Revance Therapeutics
Rex Energy
Rexnord
Rice Energy
RigNet
RingCentral
RiskMetrics
Ritter Pharmaceuticals
Rocket Fuel
Roka Bioscience
Rosetta Genomics
Rosetta Stone
RPX Corporation
RSC
RSP Permian
Rubicon Technology
Ruckus Wireless
rue21

S
Sabre
Sage Therapeutics
Sagent Pharmaceuticals
Salary.com
Sanchez Energy
SandRidge Energy
Santander Consumer USA
SciQuest
SCYNEXIS
SeaWorld Entertainment
SemiLeds
Semler Scientific
SenoRx
Sensata Technologies
Seres Therapeutics
ServiceNow
SFX Entertainment
Shopify
ShoreTel
Shutterstock
Sientra
Signal Genetics
Silvercrest Asset Management
Sirtris
Skilled Health
Skullcandy
Smart Final Stores
SMART Technologies
SolarCity
Solazyme
SoundBite Communications
Sourcefire
Spark Energy
Spark Therapeutics
Spirit Airlines
Splunk
Sportsmans Warehouse
Springleaf
Sprouts Farmers Markets
SPS Commerce
Square
Square 1 Financial
SSC Technologies
SteadyMed
Stemline Therapeutics
Stock Building Supply
Stonegate Mortgage
STR
SuccessFactors
Summit Materials
SunCoke Energy
SunEdison Semiconductor
Sunrun
Super Micro Computer
Superior Offshore International
Surgery
Surgical Care Affiliates
Swift
Switch and Data
Symetra Financial
Synacor
Synta Pharmaceuticals

T
T2 Biosystems
Tableau Software
Talmer
Taminco
Tandem Diabetes Care
Tangoe
Targanta Therapeutics
Taylor Morrison Home
TCP International
Team Health
Teavana
TechTarget
Teladoc
TeleNav
Tengion
TESARO
Tesla Motors
TetraLogic Pharmaceuticals
Tetraphase Pharmaceuticals
Textainer
Textura
The Active Network
The Ensign
The Fresh Market
The New Home Company
The Rubicon Project
Thermon
Third Point Reinsurance
Tillys
Titan Machinery
TMS International
Tokai Pharmaceuticals
TomoTherapy
Tornier
Tower International
Townsquare Media
Tracon Pharmaceuticals
TranS1
TransUnion
Travelport Worldwide
Tremor Video
Trevena
TRI Pointe Homes
TriMas
TriNet
Trinseo
TriState Capital
Triumph
Trius Therapeutics
TrueCar
Trulia
Trupanion
TubeMogul
Tumi
Twitter

U
U.S. Silica
Ubiquiti Networks
UCP
Ultragenyx Pharmaceutical
Unique Fabricating
uniQure
Univar
Upland Software

V
Validus
Vanguard Health Systems
Vantiv
Varonis Systems
Vascular Biogenics
Veeva Systems
Vera Bradley
Veracyte
Verastem
Veraz Networks
Veritex
Versartis
Verso Paper
Viking Therapeutics
Vince
Violin Memory
Virgin America
Virgin Mobile USA
Virtusa
Vitae Pharmaceuticals
Vital Therapies
Vitamin Shoppe

Vivint Solar
VMware
Vocera Communications
Voltaire
Voyager Therapeutics

W
Walker Dunlop
Wave Life Sciences
Wayfair
WCI Communities
Wesco Aircraft
Western Gas
William Lyon Homes
Wingstop
Wix.com
Workday

X
Xactly
Xencor
Xenon Pharmaceuticals
XOOM
XTENT
Xtera Communications

Y
Yandex
Yelp!
Yodlee
YuMe

Z
ZAFGEN
Zayo
ZELTIQ Aesthetics
Zendesk
Zillow
Zipcar
Zoe's Kitchen
Zosano Pharma
ZS Pharma
zulily
Zynga

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3PAR
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