In Search of Attention*

Zhi Da[†], Joseph Engelberg[‡] and Pengjie Gao[§]

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Abstract

We propose a new and direct measure of investor attention using search frequency in Google (SVI). In a sample of Russell 3000 stocks from 2004 to 2008, we find that SVI (1) is correlated with but different from existing proxies of investor attention; (2) captures investor attention in a more timely fashion and (3) likely measures the attention of retail investors. An increase in SVI predicts higher stock prices in the next two weeks and an eventual price reversal within the year. It also contributes to the large first-day return and long-run underperformance of IPO stocks. Our results provide direct support for Barber and Odean's (2008) price pressure hypothesis and highlight the usefulness of search data which can reveal investor interests.

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[†]Finance Department, Mendoza College of Business, University of Notre Dame. E-mail: zda@nd.edu; Tel: (574) 631-0354.

[‡]Finance Department, Kenan-Flagler Business School, University of North Carolina at Chapel Hill. E-mail: joseph_engelberg@kenan-flagler.unc.edu; Tel: (919) 962-6889.

[§]Finance Department, Mendoza College of Business, University of Notre Dame. E-mail: pgao@nd.edu; Tel: (574) 631-8048.

"What information consumes is rather obvious: it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."

— Herbert Simon, Nobel Laureate in Economics

1 Introduction

Traditional asset pricing models assume that information is instantaneously incorporated into prices when it arrives. This assumption requires investors allocate sufficient attention to the asset. In reality, attention is a scare cognitive resource (Kahneman, 1973), and investors have limited attention. Recent studies provide a theoretical framework in which limited attention can affect asset pricing statics as well as dynamics.[1]

When testing theories of attention, empiricists face a substantial challenge: we do not have direct measures of investor attention. We have indirect proxies for investor attention such as extreme returns (Barber and Odean, 2008), trading volume (Barber and Odean, 2008; Gervais, Kaniel, and Mingelgrin, 2001; and Hou, Peng, and Xiong, 2008), news and headlines (Barber and Odean, 2008; and Yuan, 2008), advertising expense (Chemmanur and Yan, 2009; Grullon, Kanatas, and Weston, 2004; and Lou, 2008), price limit (Seasholes and Wu, 2007). These proxies make the critical assumption that if a stock's return or turnover was extreme or its name was mentioned in the news media, then investors should have paid attention to it. However, return or turnover can be driven by factors unrelated to investor attention and a news article in the *Wall Street Journal* does not guarantee attention unless investors actually read it. This is especially true in the so-called information age where "a wealth of information creates a poverty of attention."

In this paper, we propose a novel and *direct measure* of investor attention using aggregate search frequency in Google and then revisit the relation between investor attention and asset prices. We use aggregate search frequency in Google as a measure of attention for several reasons. First, internet users commonly use a search engine to collect information, and Google continues to be the favorite. In February of 2009, Google accounted for 72.1 percent of all search queries performed in the United States.[2] Thus the search volume reported by Google is likely to be representative of the

[1] See for example, Merton (1987), Sims (2003), Hirshleifer and Teoh (2003) and Peng and Xiong (2006).
[2] Source: Hitwise (http://www.hitwise.com/press-center/hitwiseHS2004/google-searches-feb-09.php)

internet search behavior of the general population. Second, and more critically, search is a *revealed* attention measure: if you search for a stock in Google, you are undoubtedly paying attention to it. Therefore, aggregate search frequency in Google is a direct and unambiguous measure of attention. For instance, Google's Chief Economist Hal Varian recently suggested that search data has the potential to describe interest in a variety of economic activities in real time. Choi and Varian (2009) support this claim by providing evidence that search data can predict home sales, automotive sales and tourism. In a recent study, Ginsberg et al. (2008) found that search data for forty-five terms related to influenza predicted flu outbreaks one to two weeks before Centers for Disease Control and Prevention (CDC) reports. The authors conclude that, "harnessing the collective intelligence of millions of users, Google web search logs can provide one of the most timely, broad-reaching influenza monitoring systems available today."

Google makes public the Search Volume Index (SVI) of search terms via its product Google Trends (http://www.google.com/trends). Weekly SVI for a search term is the number of searches for that term scaled by its time-series average. Figure 1 plots the weekly SVI of the two search terms "diet" and "cranberry" during the period from January 2004 to February 2009. The news reference volumes are also plotted in the bottom of the figure. SVI appears to capture attention well. The SVI on "diet" falls during the holiday season and spikes at the beginning of the year. This is consistent with the notion that individuals pay less attention to dieting during the holidays (November and December) but more attention in January as part of a New Year's resolution. The SVI on "cranberry" spikes in November and December, coinciding with the Thanksgiving and Christmas holidays.

In order to measure attention paid towards particular stocks, we examine the SVI for stock ticker symbols (e.g., "AAPL" for Apple Computer, and "MSFT" for Microsoft). After obtaining the SVI associated with stock ticker symbols for all Russell 3000 stocks, we proceed in three steps. First, we investigate how SVI is related to existing attention measures. We find the time series correlations between (log) SVI and alternative weekly measures of attention such as extreme return, turnover and news are positive on average but the level of the correlation is low. In a vector autoregression (VAR) framework, we find that (log) SVI actually leads alternative measures such as extreme returns and news, consistent with the notion that investors may start to pay attention to a stock in anticipation of a news event. When we focus on our main variable, abnormal SVI (ASVI), defined as (log) SVI during the current week minus the (log) median SVI during the previous eight weeks, we find that majority of the time-series and cross-sectional variation in ASVI remain unexplained by alternative measures of attention. We also find that a stock's SVI has little correlation with a news-based measure of investor sentiment.

Second, we ask the question: whose attention is SVI capturing? Consistent with intuition, we find strong evidence that SVI captures the attention of individual/retail investors. Using retail order execution from SEC Rule 11Ac1-5 (Dash-5) reports, we establish a strong and direct link between SVI changes and trading by retail investors. Interestingly, across different market centers, the same increase in SVI leads to greater individual trading in the market center that typically attracts less sophisticated retail investors (i.e., Madoff) than in the market center that attracts more sophisticated retail investors (i.e., NYSE for NYSE stocks and Archipelago for NASDAQ stocks). This difference suggests that SVI likely captures the attention of less-sophisticated individual investors.

Third, having established the fact that SVI captures retail investor attention we test the attention theory of Barber and Odean (2008). Barber and Odean (2008) argue that individual investors are net buyers of attention-grabbing stocks and thus an increase in individual investor attention results in temporary positive price pressure. The reasoning behind the argument goes as follows. When individual investors are buying they have to choose from a large set of available alternatives. However, when they are selling, they can only sell what they own. This means that shocks to retail attention should, on average, lead to net buying from these uninformed traders. Under Barber and Odean (2008), a positive Abnormal SVI (ASVI) should predict higher stock prices temporarily and price reversals in the long run. Furthermore, we expect to find stronger attention-induced price pressure among stocks where individual investor attention matters the most.

Our empirical results which deploy ASVI as a measure of retail attention strongly support the hypotheses of Barber and Odean (2008). Among our sample of Russell 3000 stocks, a one standard deviation increase in ASVI this week leads to a positive price change of more than 30 basis points (bps) during the subsequent two weeks. This initial positive price pressure is almost completely reversed by the end of the year. In addition, we find such price pressure to be stronger among Russell 3000 stocks that are associated with smaller market capitalization and traded more by individual investors. The fact that we document strong price pressure associated with SVI even after controlling for a battery of alternative attention measures highlights the incremental value of

SVI. In fact, ASVI is the only variable that predicts both a significant initial price increase and the subsequent price reversal.

A natural venue to test the retail attention hypothesis is a stock's initial public offering (IPO). IPOs follow the pattern predicted by the attention-induced price pressure hypothesis. As studied in Loughran and Ritter (1995, 2002), among many others, IPOs usually experience temporarily high returns followed by longer-run reversal. Moreover, many authors have suggested these two stylized features of IPO returns are related to the behavior of retail investors (Ritter and Welch (2002), Ljungqvist, Nanda and Singh (2006) and Cook, Kieschnick and Van Ness (2006)). Because search volume exists prior to the IPO while other trading-based measures do not, SVI offers a unique opportunity to empirically study the impact of retail investor attention on IPO returns.

We find considerable evidence that retail attention - as measured by search volume - is related to IPO first-day returns and subsequent return reversal. First, we find that searches related to IPO stocks increase by almost 20 percent during the IPO week. The jump in SVI indicates a surge in public attention consistent with the marketing role of IPOs documented by Demers and Lewellen (2003). When we compare the group of IPOs that experience large positive ASVI during the week *prior to* the IPO to the group of IPOs that experience smaller ASVI, we find that the former group outperforms the latter by 6 percent during the first day after the IPO and the outperformance is statistically significant. We also document significant long-run return reversals among IPO stocks that experience large increases in search prior to their IPOs and large first-day returns after their IPOs. These patterns are confirmed using cross-sectional regressions after taking into account a comprehensive list of IPO characteristics, aggregate market sentiment, and an alternative attention measure – media coverage – as discussed in Liu, Sherman and Zhang (2009). Our results, however, are different from those in Liu, Sherman and Zhang (2009) who find that increased pe-IPO investor attention as measured by media coverage does not lead to price reversal or underperformance in the long run. The difference in these two paper's findings highlights the subtleties between news-based and search-based measures of investor attention.

The rest of the paper is organized as follows. Section 2 describes data sources and how we construct the aggregate Google search volume index (SVI) variable. Section 3 compares our SVI measure to alternative proxies of investor attention and examines additional factors that drive our SVI measure. Section 4 provides direct evidence that SVI captures the attention of retail investors.

Section 5 tests the price pressure hypothesis of Barber and Odean (2008) in various settings. Section 6 concludes.

2 Data and Sample Construction

Google Trends provides data on search term frequency dating back to January 2004. For our analysis, we download the weekly search volume index (SVI) for individual stocks. To make the data collection and cleaning task manageable, we focus on stocks in the Russell 3000 index for most of the paper. The Russell 3000 index contains the 3,000 largest companies, representing more than 90 percent of the total U.S. equity market capitalization. We obtain the membership of the Russell 3000 index directly from Frank Russell and Company. To minimize survivorship bias and the impact of index addition and deletion, we examine all 3,606 stocks that were ever included in the index during our sampling period from January 2004 to June 2008. As Russell 3000 stocks are relatively large stocks, our results are less likely to be affected by bid-ask bounce. To further alleviate market microstructure related concerns, we exclude stock / week observations when the market price is less than three dollars when testing the attention-induced price pressure hypothesis.

Our next empirical choice concerns the identification of a stock in Google. A search engine user may search for a stock in Google using either its ticker or company name. Identifying search frequencies by company name may be problematic for two reasons. First, investors may search the company name for reasons unrelated to investing. For example, one may search "Best Buy" in order to do online shopping rather than to collect financial information about the firm. This problem is more severe if the company name has multiple meanings (e.g. "Apple" or "Amazon"). Second, different investors may search the same firm using several variations of its name. For example, American Airlines is given a company name of "AMR Corp." in CRSP. However, investors may search for the company in Google using any one of the following: "AMR Corp", "AMR", "AA" or "American Airlines".

Searching for a stock using its ticker is less ambiguous. If an investor is searching "AAPL" (the ticker for Apple Computer Inc.) in Google, it is more likely that she is interested in financial information about the stock of Apple Inc. Since we are interested in studying the impact of investor attention on trading and asset pricing, this is precisely the group of people whose attention we would like to capture. Since a firm's ticker is always uniquely assigned, identifying a stock using its ticker also avoids the problem of multiple reference names. For these reasons, we choose to identify a stock using its ticker for the majority of our study. The only exception is when we examine IPO stocks. Because the ticker is not widely available prior to the IPO, we search for the company using its company name.

However we are cautious about using the ticker if it has a generic meaning such as "GPS", "DNA", "BABY", "A", "B", and "ALL". We manually go through all the Russell stock tickers in our sample and flag such "noisy" tickers. These tickers are usually associated with abnormally high SVIs that may have nothing to do with investor attention to the stocks with these ticker symbols. While we report the results using all tickers to avoid subjectivity in sample construction, we confirm that our results are robust to the exclusion of these "noisy" tickers (about 7 percent of all Russell 3000 stocks).

To illustrate the ticker SVI, Panel B of Figure 1 plots the SVI on Apple's ticker (AAPL) against that on Microsoft (MSFT). Two interesting observations emerge from this figure. First, we observe spikes in the SVI of "AAPL" in the beginning of a year. These spikes are consistent with increasing public attention coming from (1) the MacWorld conference which is held during the first week of January and (2) awareness of the company after receiving Apple products as holiday gifts. Second, SVIs are correlated with but remain different from news coverage. These two observations again support our argument that SVI indeed captures investor attention and is different from existing proxies of attention.

To collect data on all stocks in the Russell 3000, we employ a webcrawling program that inputs each ticker and uses the Google Trends' option to download the SVI data into a CSV file.[3] We do this for all 3,606 stocks in our sample. This generates a total of 834,627 firm-week observations. Unfortunately, Google Trends does not return a valid SVI for some of our queries. If a ticker is rarely searched, Google Trends will return a 0 value for that ticker's SVI. Of our 834,627 firm-week observations, 468,413 have valid (non-zero) SVI.

[3] To increase the response speed, Google currently calculates SVI from a random subset of the actual historical search data. This is why SVIs on the same search term might be slightly different when they are downloaded at different points in time. We believe that the impact of such sampling error is small for our study and should bias against finding significant results. When we download the SVIs several times and compute their correlation, we find the correlations to be usually above 97%. In addition, we also find if we restrict our analysis to a subset of SVIs where the sampling error standard deviation (provided by Google) is low, we get stronger results.

For comparison, we also collect two other types of SVI. First, we collect SVIs based on company name (*Name_SVI*). We have two independent research assistants report how they would search for each company based on the company name in CRSP. Where there are differences between the reports, we use Google Insights "related search" feature to determine which query is most common.[4] Unlike SVI, *Name_SVI* is clearly affected by subjectivity. Second, we collect SVIs based on the main product of the company (PSVI). To identify the main product, we follow the steps described in Da, Engelberg and Gao (2010). We begin by gathering data on firm products from Nielsen Media Research (NMR) which tracks television advertising for firms. NMR provides us a list of all firms which advertised a product on television during our sample period between 2004 and 2008. We hand-match the set of firms covered in NMR to our Russell 3000 stock sample. For each firm we select its most popular product as measured by the number of ads in the Nielsen database. Then, we consider how the main product might be searched in Google. We do this again by having two independent research assistants report how they would search for each product. Where there are differences between the reports, we use Google Insights "related search" feature to determine which query is most common.

Our main news data come from Dow Jones and consist of all *Dow Jones News Service* (DJNS) articles and *Wall Street Journal* articles about Russell 3000 firms over our sample period. Each article in the dataset is indexed by a set of tickers which we date-match to CRSP. A News observation at the weekly (monthly) level in our dataset corresponds to a firm having an article in the archive during that week (month). To disentangle news from coverage (or less important stories from more important ones), we follow Tetlock (2009) and introduce a variable called Chunky News which requires that a particular story have multiple messages (i.e., the story is not released all at once but in multiple "chunks"). According to Tetlock (2009), "...stories consisting of more newswire messages are more likely to be timely, important, and thorough." Finally, because Dow Jones News Archive (DJNA) database does not index (by ticker) a company's news media coverage prior to its initial public offering, we manually searched Factiva to obtain the media coverage attributes for the IPO sample.

[4] For each term entered into Google Insights (http://www.google.com/insights/) it returns ten "top searches" related to the term. According to Google, "Top searches refer to search terms with the most significant level of interest. These terms are related to the term you've entered... our system determines relativity by examining searches that have been conducted by a large group of users preceding the search term you've entered, as well as after."

We collect all initial public offerings (IPOs) of common stocks completed between January 2004 and December 2007 in the United States from the Thompson Financial / Reuters Securities Data Corporation (SDC) new issue database. We exclude all unit offerings, close-end funds, real estate investment trusts (REITs) , American Deposit Receipts (ADRs), limited partnerships and all stocks where the final offering price is below five dollars. We require the stock to be common shares traded on the NYSE, AMEX or NASDAQ exchange with a valid close-price within five days of the date of the IPO.

We obtain the original SEC Rule 11Ac1-5 (Dash-5) monthly reports from Market System Incorporated (MSI, now a subsidiary of Thomson Financial / Reuters), which aggregates the monthly Dash-5 reports provided by all market centers in the US and provides various transaction cost and execution quality statistics based on the Dash-5 reports. The main variables of interests from the MSI database include the number of shares executed and the number of order executed by each market center.

Other variables are constructed from standard data sources. Price and volume related variables are obtained from CRSP; accounting information is obtained from COMPUSTAT; and analyst information is obtained from I/B/E/S.

3 What Drives SVI?

In this section, we examine what drives SVI and compare SVI to other common proxies of attention. We first present simple contemporaneous correlations among (log) SVI and other variables of interest measurable at a weekly frequency in Table 1. These correlations are first computed in time series for each stock with a minimum of one year of data and then averaged across stocks. The lower triangle reports correlations for Russell 3000 stocks with below-median market capitalizations and the upper triangle reports correlations for Russell 3000 stocks with above-median market capitalizations.

The other variables of interest include the following: *Name_SVI* is the aggregate search frequency based on company name. *Absolute Abn Ret* is the absolute value of the concurrent week characteristic-adjusted abnormal return following Daniel, Grinblatt, Titman, and Wermers (1997, DGTW hereafter). In essence, this characteristic-adjustment procedure captures whether a stock outperforms average stocks with similar book-to-market, size and past return characteristics. *Abnormal Turnover* is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007), which removes time trends and seasonalities in the raw share turnovers time series. *News* refers to the number of news stories in the Dow Jones news archive in the concurrent week. *ChunkyNews* refers to the number of news stories with multiple story codes in the Dow Jones news archive in the concurrent week. Following Tetlock (2007), we construct media-based stock-level sentiment measures. For each stock in each week, we gather all the news articles about the stock recorded in the Dow Jones archive, and identify words with "negative sentiment". We count the total number of words over the entire collection of news articles about the stock (excluding so-called "stop words") within that week, and count the total number of "negative sentiment" words. Then we take the ratio of the number of "negative sentiment" words to the total number of words to get the fraction of negative words. *Frac_Neg_H4* is the fraction when "negative sentiment" words are defined using the Harvard IV-4 dictionary and *Frac_Neg_LM* is the fraction when "negative sentiment" words are identified in Loughran and McDonald (2010).

In general, the correlations between SVI and other variables of interest are low. The correlation between log SVI and log *Name_SVI* is about 9%. Again, this is because people may search company name for many reasons such as gathering product information, looking for store location or looking for a job while people who search for stock tickers are interested in financial information about the stock. In addition, different people may use different search terms when they search for a company which introduces more noise to *Name_SVI*.

Extreme returns and trading volume are popular measures of investor attention. Although they have a correlation of more than 30% with each other, their correlation with SVI is positive but small. For example, the correlation between *Absolute Abn Ret* and log SVI is 4.8% among small Russell 3000 stocks and 6.9% among big stocks. The correlation between *Abnormal Turnover* and log(SVI) is 2.6% among small stocks and 4.5% among big stocks. Such low correlation in part may be attributed to the fact that both return and turnover are equilibrium outcomes and are functions of many other economic factors in addition to investor attention.

News media coverage is another popular measure of investor attention. Anecdotal evidence presented in Figure 1 clearly indicates a positive correlation between SVI and news. We confirm this positive correlation on average between SVI and news coverage (news) and news events (chunky news). These correlations are low, ranging from 2.3% to 6.5%. There are several reasons for such low correlations. First, overall newspaper coverage is surprisingly low. Fang and Peress (2009) report that over a quarter of NYSE stocks are not featured in the press in a typical year. The number is even higher for NASDAQ stocks, which is about fifty percent. While SVI measures investor attention continuously over the year, news coverage on a typical firm is rather infrequent and sporadic. Such sporadic coverage is a bigger problem for smaller stocks, explaining the lower correlations between SVI and news variables among small Russell 3000 stocks. Second, news coverage does not guarantee attention unless investors actually read it and the same amount of news coverage may generate a different amount of investor attention across different stocks. Even if a surge in SVI is completely triggered by a news event, SVI carries additional useful information about the amount of attention the news event ultimately generates among investors.

Another variable of interest is investor sentiment, which according to Baker and Wurgler (2007), is broadly defined as "a belief about future cash flows and investment risks that is not justified by the facts at hand." *A prior*, it is not clear how investor attention and sentiment should be related to each other. On the one hand, since allocating attention is a necessary condition for generating sentiment, increased investor attention, especially that coming from "noise" traders prone to behavioral biases, will likely lead to stronger sentiment, and more salient impact on asset prices. On the other hand, increase attention paid to genuine news may speed up the incorporation of information to prices and attenuate sentiment. Empirically, extreme negative sentiment can be captured by counting the fraction of "negative sentiment" words in the news articles about a company. When we examine the time-series correlation between SVI and such sentiment measures ($Frac\_Neg\_H4$ and $Frac\_Neg\_LM$), we again find the correlation to be on the lower end, ranging from 1.2% to 2.7%.

We then examine the weekly lead-lag relation among measures of attention using a vector autoregression (VAR). For this exercise, we only include variables that are observable at a weekly frequency. The four variables include *Log(SVI)*, the natural logarithm of weekly SVI; *Log(turnover)*, the natural logarithm of weekly turnover; *Absolute Abnormal Return*, the absolute value of the concurrent week DGTW abnormal return; and *Log(1+Chunky News)*, the natural logarithm of one plus the number of chunky news during that week. Note that we define all four variables using only contemporaneous information within the week so that no spurious lead-lag relation will be generated because of variable construction. We run the VAR for each stock with at least two years of weekly data. We include both a constant and a time trend in the VAR. The VAR coefficients are then averaged across stocks and reported in Table 2 with the associated p-values. To account for both time-series and cross-sectional correlation in the error terms, these p-values are computed using a block bootstrap procedure under the null hypothesis that all VAR coefficients are zero. We start with the panel of residuals from the VAR and construct 10,000 bootstrapped panels. In the time series dimension, we block-bootstrap with replacement using a block length of 23 weeks to preserve the autocorrelation structure in the error terms. In the cross-sectional dimension, we also bootstrap with replacement. We repeat the VAR estimation in each bootstrapped panel, which allows us to build up the empirical distribution of the VAR. Overall, our block bootstrap procedure is similar to those used in a recent paper by Bessembinder, Maxwell, and Venkataraman (2006). A simple reverse Fama and MacBeth method that does not account for cross-autocorrelations in error terms produces even smaller p-values.[5]

We find that SVI leads the other three attention proxies. The coefficients on lagged log(SVI) are all positive and are statistically significant when we have current-week *Log(turnover), Absolute Abnormal Return* and *Log(1+Chunky News)* as the dependent variables. These positive coefficients suggest that SVI captures investor attention in a more timely basis than extreme returns or news. This finding should not surprise us. To the extent that investors trade only after paying attention to a stock and their trading causes price pressure persisting over a week, SVI could lead turnover and extreme returns. In addition, since investors may start to pay attention to a stock and search in Google well ahead of a pre-scheduled news event (e.g. an earnings announcement), SVI could also lead news-related variables. In the other direction, we find lagged *Log(turnover)* and *Log(1+Chunky News)* to be significantly but negatively related to current-week *Log(SVI)*. This is likely due to mean-reversion in SVI after major news and high turnover during which SVI spikes. We also find lagged *Absolute Abnormal Return* to be significantly and positively related to current-week *Log(SVI)*, consistent with the idea that investors continue to pay more attention to a stock after a week of extreme returns.

Finally, we examine the relation between SVI and other proxies of attention in a set of regres-

[5] The reverse Fama-MacBeth regression carries out time-series regression first, then takes the cross-sectional averages of regression coefficients from the first-stage regressions.

sions. Our key variable of interest in the paper – Abnormal SVI (ASVI) – is defined as:

$$ASVI_t = \log(SVI_t) - \log[Med(SVI_{t-1}, ..., SVI_{t-8})], \quad (1)$$

where $\log(SVI_t)$ is the logarithm of SVI during week t, and $\log[Med(SVI_{t-1}, ..., SVI_{t-8})]$ is the logarithm of the median value of SVI during the prior eight weeks.[6] Intuitively, the median over a longer time window captures the "normal" level of attention in a way that is robust to recent jumps. ASVI also has the additional advantage that time trends and other low-frequency seasonalities are removed. A large positive ASVI clearly represents a surge in investor attention and can be compared across stocks in the cross-section.

We report panel regression results in Table 3 where the dependent variable is always ASVI. All regressions reported in this table contain week fixed-effects, and the standard errors are clustered by firm. We confirm that the ASVI is positively related to both the size of the stock, extreme stock returns and abnormal turnover. Comparing regressions 1 and 2, we find that the *Chunky News Dummy* is more important in driving ASVI than the *News Dummy*, suggesting that the occurrence of news (rather than news coverage) matters. The regression coefficient on *Log(Chunky News Last Year) is* negative and significant, suggesting that a stock with lots of recent news coverage is less likely to receive "unexpected" attention. Finally, the R-squared of these regressions are only about 3.3 percent, suggesting that existing proxies of attention only explain a small fraction of the variation in the ASVI. It is also possible that some variation in ASVI could also be driven by measurement error and other noise. In the latter case, such noise and measurement errors are likely to bias against us finding any reliable results.

In summary, we find that SVI is related to but different from alternative proxies of attention proposed in the literature, consistent with the distinct feature of SVI in capturing the *demand* for attention or *active* attention on a real-time basis.

[6] Unreported analysis confirms that our main results are robust to the length of the rolling window (4 weeks, 6 weeks, 10 weeks, etc.).

4 SVI and Individual Investors

Whose attention is captured by SVI? Intuitively, people who search financial information related to a stock in Google are more likely to be individual or retail investors since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg.[7] In this section, we provide direct evidence that changes in investor attention measured by SVI are indeed related to trading by individual investors.

Traditionally, trade size from ISSM and TAQ databases are used to identify retail investor transactions (see Easley and O'Hara, 1987, for theoretical justification and Lee and Radhakrishna, 2000; Hvidkjaer, 2008; Barber, Odean and Zhu, 2008, among others for empirical evidence). However, after decimalization in 2001, order splitting strategies become prominent (see Caglio and Mayhew, 2008). Hvidkjaer (2008) shows that retail trade identification becomes ineffective after 2001 and provides a detailed discussion of this issue. Because our sample of SVI begins in January 2004, we are not able to infer retail investor stock transactions directly from TAQ using trade sizes.

Instead, we obtain retail orders and trades directly from Dash-5 monthly reports. Since 2001, by Rule 11Ac1-5 and the subsequent Regulation 605, the United States Security and Exchange Commission (SEC) requires every market center to make public monthly reports of statistical information concerning the "covered orders" they received for execution. The "covered orders" primarily come from individual / retail investors because they exclude any orders for which the customer requests special handling for execution. There should be few institutional orders because institutions typically use so-called "not-held-orders" which are precluded from the Dash-5 reporting requirement. In addition, all order sizes greater than 10,000 shares are not presented in the Dash-5 data. This further reduces the likelihood of having any institutional orders in the Dash-5 data.[8] Boehmer, Jennings and Wei (2007) provide additional background on the Dash-5 data including details about trading volume, number of orders, and transaction costs (by different market centers as well as aggregated across market centers). To save space, we do not repeat their analysis here and direct interested readers to their paper.

[7] For example, we find that there is a significant jump in weekly SVI of about 10% (t-statistics > 9) for stocks picked by Jim Cramer in the CNBC's Mad Money Show. Engelberg, Sasseville and Williams (2008) argue that it is mainly individual investors whose attention the show is capturing.

[8] Interested readers are encouraged to consult SEC Regulation 605 for the reporting requirements of participating market centers. Harris (2003. p.82) has a detailed discussion of "not-held-orders".

For our purposes, we only consider the subset of "covered orders" that are market and marketable limit orders which are more likely to be retail orders demanding liquidity. The information contained in the Dash-5 reports includes number of shares traded, number of orders received, and various dimensions of execution quality by order size and stock. Specifically, the monthly Dash-5 reports disaggregate the trading statistics into four categories: (1) 100 – 499 shares; (2) 500 – 1,999 shares; (3) 2000 – 4,999 shares; and (4) 5,000 – 9,999 shares.

The Dash-5 reports allow us to compute monthly changes in orders and turnovers from individual investors. We then relate these changes to monthly changes in SVIs in Table 4. The monthly SVI is computed by aggregating weekly SVIs assuming daily SVI is constant within the same week. We consider several alternative proxies of attention as control variables: *Log(Market Cap)* is the logarithm of the prior month-end (t-1) market capitalization; *RET(t)* is the monthly return from the current month (t); $|RET(t)|$ is the absolute value of the return of the stock during month (t); *Chunky News Dummy* is equal to one if there is at least one chunky news story in the Dow Jones News archive during month (t) and zero otherwise; and *Advert. Expense/Sales* is the latest advertisement expenditure to sales ratio available from COMPUSTAT prior to month (t), where we set advertisement expenditure equal to zero if advertisement expenditure is missing in COMPUSTAT.

We also control for other stock characteristics that might be related to turnover. These stock characteristics include: *B/M* is the book to market value of equity, where the book value of the equity is from the latest available accounting statement and the market value of equity is the month-end close price times the number of shares outstanding at the end of month (t-1); *Non-institutional Holding* is one minus the percentage of stocks held by all S34-filing institutional shareholders at the end of the quarter prior to the current quarter; *Return Volatility* is the standard deviation of the individual stock return estimated from daily returns during quarter (Q-1); Δ *[log(Turnover)]* is the difference between the natural logarithm of total stock turnover reported by CRSP in month (t-2) and month (t-1); *RET(t-1)* is the one-month return prior to current month t; *RET[t-13, t-2]* is the cumulative stock return between months (t-13) and (t-2); and *RET[t-36, t-14]* is the cumulative stock return between months (t-36) and (t-14).

In Panel A of Table 4, we examine changes in individual trading across all markets centers. We first consider the smaller order size categories (100 – 1,999 shares) in the Dash-5 reports which are more likely to capture retail transactions. When we measure changes in individual trading as changes in the number of orders (in logarithm), we find that a one-percent increase in the SVI leads to 0.0925 percent increase in individual orders (regression 1). This positive correlation is statistically significant at the 1 percent level after controlling for alternative proxies of attention and other trading-related stock characteristics. It is not too surprising that several alternative proxies of attention are also significant but they might be mechanically related to trading. For example, trading can correlate with absolute returns or market capitalizations via price impact, and trading can correlate with news if news coverage is triggered by abnormal trading. In regression 2, we measure changes in individual trading by changes in turnover (in logarithm) and find a similar relation between the change in individual trading and the change in SVI. Finally, we use all order size categories (100 – 9,999 shares) in the Dash-5 reports. We find almost identical results as reported in regressions 3 and 4 in Panel A of Table 4 and we therefore use all order size categories hereafter.

Individual investors differ in their level of financial sophistication, but measuring the financial sophistication in general is difficult (see Calvet, Campbell and Sodini, 2009 for a recent attempt to measure household financial sophistication in Sweden). In an effort to identify the relative financial sophistication of investors, we rely on the differences of transaction costs and transaction qualities across different market centers. In particular, empirical evidence offered by Battalio (1997), Battalio, Greene and Jennings (1997), and Bessembinder (2003) suggests that retail orders from different individual investors may be routed to and executed at different market centers based on the information content in the orders. Therefore, retail orders from less sophisticated individual investors are often routed to and executed at market centers that pay for order flow. One well-known market center is the now defunct Madoff Securities LLC (Madoff). In contrast, orders from more sophisticated investors often go to the New York Stock Exchange (NYSE) for NYSE stocks and Archipelago for NASDAQ stocks. These venues do not pay for order flow and they are typically the execution venues of last resort. As a result, by examining the change in individual trading at different market centers separately, we can make inferences about which groups of individual investor attention SVI may capture. Our working hypothesis is that, for less sophisticated investor clienteles, we are more likely to see a large increase in order number and share volume for a similar magnitude change in SVI.

We repeat our regressions separately for Madoff and NYSE/Archipelago in Panel B of Table 4.

Interestingly, we find the correlation between the change in individual trading and the change in SVI is much stronger at Madoff. After controlling for alternative proxies of attention and other trading-related stock characteristics, a 1 percent increase in SVI translates to a 0.264 percent increase in individual orders and a 0.297 percent increase in individual turnover at Madoff (regressions 1 and 2). Such an increase in individual trading is much higher than the average increase across all market centers as reported in Panel A (where the corresponding increases are 0.103 percent and 0.131 percent). In contrast, the same 1 percent increase in SVI only translates to a 0.092 percent increase in individual orders and a 0.104 percent increase in individual turnover at NYSE/Archipelago (regressions 3 and 4). Finally, we directly examine the difference in retail trading between Madoff and NYSE/Archipelago using a matched sample in regressions 5 and 6. Each month, we focus on a set of stocks that are traded on both Madoff and NYSE/Archipelago. We create a dummy variable *Madoff* which takes value the value one for all observations from Madoff and zero for all observations from NYSE/Archipelago. In this matched sample, we find that a 1 percent increase in SVI leads to a 0.109 percent greater increase in individual orders and a 0.0951 percent greater increase in individual turnover at Madoff and these additional increases are statistically significant. It is interesting to note that the news variable actually correlates with the trading at NYSE/ARCH more than that at Madoff, suggesting that the news variable is not capturing the attention of less sophisticated retail investors.

In sum, our results suggest that SVI captures the attention of less sophisticated individual investors. In the following section, we will explore how the attention from those less sophisticated retail investors can affect asset prices.

5 SVI and Price Pressure

As seen from Figure 1, attention can vary considerably over time. How does a sharp increase in retail attention affect stock returns? Barber and Odean (2008) argue that buying allows individuals to choose from a large set alternatives while selling does not. For retail traders who rarely short, selling a stock requires individuals to have already owned the stock. Therefore, the Barber and Odean (2008) model predicts attention shocks will lead to net buying by retail traders. Because retail traders are uninformed on average, this will lead to temporarily higher returns. To the extent that ASVI is a direct measure of investor attention, we can directly test the price pressure hypothesis of Barber and Odean (2008). Specifically, we expect large abnormal SVI (ASVI) to result in increased buying pressure that pushes up stock prices temporarily. We first investigate such price pressure in the context of a cross-section of Russell 3000 stockd and then in the context of IPOs. Given the lack of trading data prior to the IPO, trade-based measures of attention are unavailable. Thus, SVI offers a unique opportunity to empirically study the impact of retail investor attention on IPO returns.

5.1 Russell 3000 Stock Sample

We first investigate the empirical relation between ASVI and future stock returns for all Russell 3000 stocks in our sample. We use a Fama-MacBeth (1973) cross-sectional regression to account for time-sepecific economy-wide shocks. Each week, we regress future DGTW abnormal returns at different horizons (measured in basis points,or bps) on ASVI and other control variables. The regression coefficients are then averaged over time and standard errors are computed using the Newey-West (1985) formula with eight lags. All variables are cross-sectionally demeaned (so the regression intercept is zero) and independent variables are also standardized (so the regression coefficient on a variable can be interpreted as the impact of one standard deviation change in that variable). These regression results are reported in Table 5.

In regression 1, the dependent variable is next-week DGTW abnormal return. We find strong evidence of positive price pressure following an increase in individual attention measured by ASVI. An one-standard-deviation increase in ASVI leads to a significant positive price change of 18.7 bps among Russell 3000 stocks.

If such price increases come from individual buying activity after they paid attention to the stock, we would expect it to be stronger among stocks that are traded more by individual investors and among stocks where noise trading has a larger price impact. This is exactly what we find in our data. For example, we find a significant and negative coefficient on the interaction term between Log Market Cap and ASVI. This negative coefficient suggests a larger price increase following an increase in ASVI among smaller Russell 3000 stocks, consistent with our conjecture that the price increase reflects price pressure since price impact of trading is usually higher among smaller stocks.

We also measure retail trading directly using $Percent\ Dash\text{-}5\ Volume$, defined as the ratio between Dash-5 trading volume and the total trading volume during the previous month. We find the interaction between this retail trading measure and ASVI is significant in predicting the first-week abnormal stock return, which suggests stronger price increase among stocks traded mainly by retail investors, again supporting the price pressure hypothesis of Barber and Odean (2008).

While the positive coefficient on ASVI in regression 1 is consistent with the price pressure hypothesis, it could also simply reflect positive fundamental information about the firm which is captured by ASVI on a more timely basis. For example suppose a company announces an innovation its product to which consumers react positively. Such a positive reaction immediately translates into a higher SVI as people start to search the company stock, which "predicts" a later price increase as this positive news get gradually incorporated into the stock price.

We have two pieces of evidence that argue against such a hypothesis First, we directly test this information story by controlling for the SVI on the main product of the company (PSVI). We define abnormal product SVI (APSVI) in the same way as ASVI. For stocks without valid APSVI, we set APSVI to be zero.

If the information story is true, we expect a even bigger positive coefficient on APSVI which subsumes the predictive power of ASVI when we include APSVI in the regression. This is not true in regression 1, the coefficient on ASVI is still positive and significant. Interestingly, the regression coefficient on APSVI is in fact negative although its magnitude is small (a -2.5 bps price drop for an one standard deviation increase in APSVI).

The positive significant coefficient on ASVI in regression 1 is also obtained after controlling for alternative measures of investor attention. Among these alternative attention measures, we find a significant positive coefficient on abnormal turnover, consistent with the high-volume return premium documented in Gervais, Kaniel, and Mingelgrin (2001). We also observe weak incremental predictive power on the Chunky News Dummy which measures whether there is news event in the current week. The weak predictive power is not due to the use of a dummy variable. In fact, if we replace the dummy news variable with a continuous news variable, the regression coefficient ceases to be significant, likely due to a nonlinear relation between the amount of investor attention and the number of related news articles.

When we examine the abnormal returns in week 2 to 4 in regression 2 to 4, we find the incremental predictive power of ASVI to persist in week 2 before disappearing afterwards. An one-standard-deviation increase in ASVI leads to a significant positive price change of 14.9 bps in week 2 then the regression coefficient drops to 3.85 bps in week 3 and becomes negative (-1.6 bps) in week 4, indicating a price reversal.

The second distinguishing feature between the price pressure hypothesis and the information-based alternative is their predictions for long-run returns. If an initial price increase is due to temporary price pressure, we would expect it to revert in the long run. If, however, the initial price increase reflect fundamental information about the firm, then no long-run reversal will be expected. It is therefore important to examine how long-run return reacts to the current-week ASVI.

We examine long-run returns in regression 5. Following Barber and Odean (2008), we skip the first month and look at the returns from week 5 to week 52. We find a negative coefficient of -28.9 bps on ASVI, similar to the magnitude of total initial price pressure in the first two weeks, suggesting that the initial price pressure is almost entirely reversed in one year. However, the negative coefficient is marginally insignificant (t-value = 1.69). This is not too surprising, given our short five-and-a-half-year sample, we do not have too many independent 48-week return observations so the regression coefficient is unlikely to be significant after the Newey-West (1985) autocorrelation correction. It is important to point out, however, ASVI seems to be the only measure of attention that predicts both the initial price increase and later long-run price reversal.

Table 6 reports the results of several robustness checks. Panel A and B report the regression results for the sampling period from January 2004 to May 2006 and the sampling period from June 2006 to June 2008, respectively. May 2006 is an interesting cutoff point since that was when Google Trends data first became available to the public as a "Google Labs" product.[9] The regression results are qualitatively similar in the two sub-sampling periods although slightly stronger in the second, potentially because as more people search in Google, SVI becomes a better and better measure of investor attention over time. Panel C of Table 6 reports the regression results after we exclude the "noisy" tickers from our sample. Since "noisy" tickers have generic meanings such as "GPS", "DNA", "BABY", "A", "B", and "ALL," they are usually associated with abnormally high SVIs which are unlikely to be missing. As a result, while they only account for about 7% of all Russell 3000 stocks in our initial sample, they account for a bigger fraction (about 20%) of our final sample

[9] This can be seen by typing "Google Trends" itself into Google Trends.

of tickers with valid SVIs. Panel C shows that removing these "noisy" tickers hardly changes our regression results.

To summarize, we find a one standard-deviation increase in ASVI to be associated with significant positive price pressure of more than 30 bps in the first two weeks, and this initial price pressure is almost completely reversed in one year. This pattern is not driven by alternative measures of attention and is less consistent with an alternative explanation based on fundamental information contained in SVI. Overall, our evidence provides strong and direct supporting evidence for the price pressure hypothesis of Barber and Odean (2008).

5.2 Initial Public Offerings (IPO) Sample

A natural venue to test the retail attention hypothesis is a stock's initial public offering (IPO). There are two stylized facts about IPO returns. First, IPOs on average have large first-day returns (see Loughran and Ritter, 2002). Second, IPOs exhibit long-run underperformance (Loughran and Ritter, 1995; Brav, Geczy, and Gompers, 2000).

Barber and Odean's (2008) attention-induced price pressure hypothesis naturally applies to IPOs because IPO stocks are likely to grab retail attention surrounding the time of going public. For the set of IPO stocks that receive more retail attention prior to the time of going public, these IPOs are likely to experience greater retail buying pressure when trading starts. Since it is usually difficult to short-sell IPOs, buying pressure from the retail investors can contribute to higher first-day returns. Subsequently, for the set of IPO stocks bid up by retail investors, when the price pressures induced by excess, retail demand dissipates, stock prices eventually reverse, resulting in long-run underperformance.

Higher first-day IPO returns and subsequent long-run underperformance are also consistent with sentiment-based explanations of Ritter and Welch (2002), Ljungqvist, Nanda and Singh (2006) and Cook, Kieschnick and Van Ness (2006). For example, Ljungqvist, Nanda and Singh (2006) and Ritter and Welch (2002) conjecture that the over-enthusiasm of retail investors may drive up an IPO's first-day return, and eventually overpriced IPOs revert to fundamental value which causes long-run underperformance. There are some circumstances in which researchers have been able to obtain the pre-IPO valuation of retail investors as a measure of retail investor sentiment. For example, using a novel dataset with valuations of a set of "when-issue" IPOs from the "grey market" in several continental European countries, Cornelli, Goldreich, and Ljungqvist (2006) find that pre-IPO valuations are positively correlated with first-day IPO return, and negatively correlated with IPO performance up to one year after going public.

There are a couple of reasons to think that *retail* investor attention and *retail* investor sentiment are positively related. First, attention is a necessary condition to generate sentiment. For a retail investor to develop sentiment and become overly enthusiastic about a forthcoming IPO, he has to first allocate attention to the IPO. Second, retail investors are likely to be "sentiment" traders suffering from various behavioral biases. Given the fact that during the IPO period, IPO stocks usually receives positive media coverage, or IPO stocks come to the market with favorable market conditions, IPO stocks that receive more retail attention are also more likely to generate positive sentiment among retail investors.

We again measure retail attention prior to the IPO using the abnormal SVI variable (ASVI). Because there is no ticker widely available prior to the IPO, we use the company name provided by the Security Data Corporation (SDC) to search for the stock in Google Trends in order to obtain the SVI. For the sample of IPOs from 2004 to 2007, we are able to identify 185 IPOs with sufficient searches so their SVIs are not missing.[10] IPOs in our sample are precisely those receiving sufficient retail attention and thus offer more statistical power to examine the relationship between pre-IPO retail attention and post-IPO stock performance.

We first confirm that there are significant changes in SVI around the time of the IPO. Panel A of Figure 2 illustrates the cross-sectional mean and median of the SVI (in logarithm) around the IPO week (week 0). We observe a significant upward trend in SVI starting two to three weeks prior to the IPO week, and there is a significant jump in SVI during the IPO week, regardless of whether we measure SVI by sample mean or median. Panel B of Figure 2 confirms the pattern using abnormal SVI (ASVI) around the IPO week. The SVI on an IPO stock jumps by 20 percent (using the mean) during the IPO week, reflecting a surge in retail attention toward the stock. This surge in retail attention is consistent with the marketing role of IPOs documented by Demers and Lewellen (2003). Interestingly, the shift in retail investor's attention is not permanent. The SVI

[10] From SDC new issue database, we can identify 571 common share IPOs traded initially on NYSE, AMEX or NASDAQ. There are two reasons why we cannot obtain valid SVI values from Google Trends some IPO stocks. First, as we pointed out, individuals may not use the SDC company name to search for the stock in Google. Second, Google Trends truncate the output and return missing values for SVIs with insfficient searches.

reverts to its pre-IPO level in two to three weeks after the IPO.

Second, we examine the relation between increased attention prior to the IPO and the first-day IPO return. Panel A of Figure 3 summarizes the main results. Consistent with the attention-induced price pressure hypothesis, the set of IPOs with low ASVI during the week prior to the IPO have first-day average returns of 10.90 percent while the set of IPOs with high ASVI have much higher first-day average returns of 16.98 percent. The difference between the two average first-day returns is about 6.08 percent. Both t-tests and nonparametric Wilcoxon tests indicate that the difference is statistically significant at the 1 percent level.

We formalize the analysis using regressions in Table 7. Regressions allow us to control for IPO characteristics and other variables that are related to first-day IPO returns. In all regressions, the dependent variable is the individual IPO's first-day return, computed as the first CRSP available closing price divided by the offering price minus one. In addition to ASVI, we examine three variables shown in prior literature to have strong predictive power for the first-day IPO return. The first variable is *Media*, defined as the logarithm of the number of news articles recorded by the Factiva (using company name as the search criteria) between one day after filing date and one day before IPO date, normalized by the days between filing day and IPO day. Both Cook, Kieschnick and Van Ness (2006) and Liu, Sherman and Zhang (2009) show that this alternative measure of attention also predicts first-day IPO return, though they differ in their intepretation of the effect of pre-IPO media coverage. The second variable is *Price Revision*, defined as the ratio of the offering price divided by the medium of the filing price. As suggested by Hanley (1993), a larger revision of the offering price is also associated with a higher first-day return. Finally, it is well known that IPOs come in waves (see Ibbotson and Jaffe, 1975; Ritter, 1984; Lowry and Schwert, 2002, among others), so aggregate positive market sentiment could drive both SVI and first-day IPO returns. While our sampling period from 2004 to 2007 is generally considered a "cold" period for IPO activities, we still control for the impact of time-varying aggregate market sentiment using the third additional variable, *DSENT*, developed in Baker and Wurgler (2006). *DSENT* is the Baker-Wurgler monthly investor sentiment change (orthogonal to macro variables) at the month when the firm goes to public, obtained from Jeffrey Wurgler's website. In contrast to *Media* and *Price Revision* which are IPO-specific, *DSENT* is an aggregate market-level variable.

We also control for a comprehensive list of firm- and industry-level characteristics in Table 7.

Log(Offering Size) is the logarithm of offering size, where the offering size is defined as the offering price multiplied by the number of shares offered. *Log(Age)* is the logarithm of years between the firm's founding year and the year of IPO, where the firm age is obtained from Jay Ritter's website and supplemented by hand-collected information from various sources. *Log(Asset Size)* is the logarithm of firm's total assets prior to IPO. *CM Underwriter Ranking* is the Carter-Manaster ranking of lead underwriter (Carter and Manaster, 1990), obtained from Jay Ritter's website. *VC Backing* is a binary indicator variable taking value of one if the IPO is backed by a venture capital firm, and zero otherwise. *Secondary Share Overhang* is defined as the secondary shares offered / (IPO share offered + secondary share offered). *Past Industry Return* is the Fama-French 48-industry portfolio return corresponding to the industry classification of the IPO at the time of public offering.

Regression 1 in Table 7 confirms that ASVI, on a stand-alone basis, strongly predicts first-day IPO return. The regression coefficient of 0.275 suggests that one standard deviation increase in ASVI (0.168) leads to a 4.62% (= 0.168 x 0.275) higher first-day return. While regression 2 confirms the predictive power of the news variable, *Media*, as documented in Liu, Sherman and Zhang (2009), ASVI seems to be a better predictor than *Media* in terms of a more significant regression coefficient and a higher R-square. Regression 3 shows that *Price Revision* is by far the strongest predictor of the first-day return. A single *Price Revision* variable explains more than 23% of the variation in first-day returns across IPOs in our sample. Finally, regression 4 suggests that changes in aggregate market sentiment does not seem to drive first-day IPO returns, which is not too surprising given that our sample period coincides with a relatively cold period for IPOs.

Regressions 4 to 8 in Table 7 control for other IPO characteristics and the predictive power of all four variables remain. In particular, in regression 5, the regression coefficient on ASVI drops slightly to 0.203, but remains highly significant. Finally, when we include all four variables in regression 9, we find ASVI drives out *Media*, consistent with the notion that SVI is the more direct and therefore the better measure of retail attention among our sample of IPOs. The regression coefficient on ASVI is 0.189, which measures the incremental predictive power of ASVI. Even after controlling for almost all existing variables affecting first-day returns,one standard deviation increase in ASVI still leads to a 3.18% (=0.168 x 0.189) higher first-day return.

Third, we examine the relation between increased retail attention prior to the IPO and the long-run performance of the IPO. Panel B of Figure 3 summarizes the main findings. The figure plots the mean and median of the market capitalization and book to market equity matched portfolio adjusted cumulative IPO returns from week 5 to 52 after the IPO. The choice of this return horizon is consistent with Figure 2 which shows that retail investor attention level largely reverts to the pre-IPO level by the end of week 4.[11] We focus on the IPOs that experience large first-day returns and further divide them into two portfolios based on ASVI prior to the IPO. This figure illustrates that IPOs with large first-day returns driven by investor attention indeed underperform firms with similar market capitalizations and book to market equity ratios. In contrast, IPOs experiencing large first-day returns without large increases in their SVI prior to IPO do not experience post-issuance return reversal. The difference between the two average first-day returns is about 9.11 percent. Both t-tests and nonparametric Wilcoxon tests indicate that the difference is statistically significant at the 1 percent level.

We formalize the analysis using cross-sectional regressions in Table 8 where we include the same additional control variables as in Table 7. Panel A reports the results when the dependent variable is the cumulative IPO raw return from week 5 to 52 post-IPO. In regression 1, we find that neither ASVI nor first-day return alone predict long-run IPO underperformance. Interestingly, the interaction between ASVI and first-day return does (as seen in regression 2). This is consistent with our conjecture that for IPOs with high first-day returns that also experienced increases in retail investor attention, the high first-day returns are partly driven by "price pressure" and will revert in the long run. In addition, the interaction term between the first-day return and *Media*, *Price Revision*, and $DSENT$ are not significant in regressions 3 to 5. As we have shown, SVI more likely captures the attention of individual retail investors while offering price revisions likely capture the attention of institutional investors. The insignificance of the offering price revision variable suggests that it is the individual investor's attention (not that of institutions) that contributes to the high first-day IPO return which is eventually reversed in the long-run.

Our results are different from those in Liu, Sherman and Zhang (2009) who find that increased investor attention pre-IPO measured using media coverage does not lead to price reversal or underperformance in the long run. Liu, Sherman and Zhang (2009) interpret newspaper article counts

[11] We also experiment skipping the first three months after the IPO to take into account the market making and price stabilization efforts by lead underwriters in that period (see Ellis, Michaely, and O'Hara, 2000 and Corwin, Harris, and Lipson, 2002). The results are qualitatively similar.

as reflecting an increase in demand from genuine (as opposed to temporary, sentiment-driven) investors. In contrast, our pre-IPO ASVI is likely to serve as a direct measure of retail investor attention which does not persist after the IPO (see Figure 2). In addition, our sample of IPOs is associated with sufficient individual investor attention so that the price-pressure-based explanation is more relevant. In fact, regression 6 in Panel A of Table 8 shows that ASVI seems to be the only variable that allows us to identify IPOs that may underperform in the long-run.

We also repeat the regression analysis using adjusted long-run stock returns post-IPO. Panel B of Table 8 reports the results where the dependent variable is the cumulative IPO raw return adjusted by cumulative industry returns over the same horizon. In Panel C, the cumulative IPO raw return is adjusted by the cumulative return of a size and book to market matched portfolio (excluding IPO stocks issued in the past five years). These return adjustments hardly change our main conclusion. The regression coefficient on the interaction term between ASVI and first-day return is always negative and significant, confirming the existence of long-run underperformance among IPOs with high first-day returns that also experienced increases in retail investor attention prior to the IPO.

To summarize, two interesting empirical results arise from the analysis of IPO stocks. First, we find that ASVI has strong incremental predictive power for the first-day IPO return. Second, ASVI also predicts long-run underperformance among IPO stocks with high first-day returns. The results are consistent with the price pressure hypothesis as described in Barber and Odean (2008).

6 Conclusion

Existing measures of investor attention such as turnover, extreme returns, news and advertising expense are indirect proxies. In contrast, we propose a new and direct measure of retail investor attention using search frequency in Google (SVI) in this paper. In a sample of Russell 3000 stocks from 2004 to 2008, we first show that SVI is correlated with but different from existing proxies of investor attention. We also provide evidence that SVI captures the attention of retail investors. Because SVI is a direct measure of individual attention, we use it to test the attention-induced price pressure hypothesis built upon Barber and Odean (2008). We find that an increase in SVI for Russell 3000 stocks predicts higher stock prices in the next two weeks and an eventual price reversal within the year. It also contributes to the large first-day return and long-run underperformance for a sample of IPO stocks.

Beyong testing theories of attention, this paper also illustrates the usefulness of search data in financial applications. To our knowledge this is the first paper to utilize a large database of internet search volume in finance. As empiricists, we rarely observe the aggregate interests of investors other than via equilibrium outcomes such as volume and return. Search volume is an objective way to to *reveal* and quantify the interests of investors and therefore should have many other potential applications in finance. We leave those endeavors for future research.

References

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, 129-151.

Barber, Brad M., and Terrance Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21(2), 785-818.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do Retail Trades Move Markets? , *Review of Financial Studies* 21(1), 151-186.

Battalio, Robert, 1997, Third Market Broker-Dealers: Cost Competitors or Cream Skimmers? *Journal of Finance* 52 (1), 341-352.

Battalio, Robert, Jason Greene and Robert Jennings, 1997, How do Competing Specialists and Preferencing Dealers Affect Market Quality? *Review of Financial Studies* 10, 969-993.

Bessembinder, Hendrik, 2003, Selection Biases and Cross-Market Trading Cost Comparisons, *Working Paper*, University of Utah.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds, *Journal of Financial Economics* 82, 251-288.

Boehmer, E., R. Jennings, and L. Wei, 2007, Public Disclosure and Private Decisions: Equity Market Execution Quality and Order Routing. *Review of Financial Studies* 20:315–58

Brav, Alon, Christopher Geczy, Paul A. Gompers, 2000, Is the abnormal return following equity issuances anomalous?, *Journal of Financial Economics* 56 (2), 209-249.

Caglio, Cecilia and Stewart Mayhew, 2008, Equity Trading and the Allocation of Market Revenue Data, *Working Paper*, U.S. Securities and Exchange Commission.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2009, Measuring the Financial Sophistication of Households, *Working Paper*, HEC School of Management, Harvard University and NBER.

Carter, Richard B., and Steve Manaster, 1990, Initial public offerings and underwriter repuation, *Journal of Finance* 45, 1045 – 1067.

Chemmanur, Thomas and An Yan, 2009, Advertising, attention, and stock returns, *Working Paper*, Boston College and Fordham University.

Choi, Hyunyoung and Hal Varian, 2009, Predicting the Present with Google Trends, *Working Paper*, Google Inc.

Cornelli, Francesca, David Goldreich, and Alexander Ljungqvist, 2006, Investor Sentiment and Pre-IPO Markets, *Journal of Finance* 61, 1187-1216.

Corwin, Shane, Jeffrey H. Harris, and Marc L. Lipson, The development of secondary market liquidity for NYSE-listed IPOs, *Journal of Finance* 59(5), 2339-2373.

Cook, Douglas O., Robert Kieschnick, and Robert A. Van Ness, 2006, On the marketing of IPOs, *Journal of Financial Economics* 82, 35-61.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2010, In search of earnings predictabilty, *Working Paper*, University of Notre Dame and University of North Carolina at Chapel Hill.

Daniel, Kent D., Mark Grinblatt, Sheridan Titman and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-Based Benchmarks, *Journal of Finance* 52, 1035-1058.

Demers, Elizabeth, and Katharina Lewellen, 2003, The marketing role of IPOs: evidence from internet stocks, *Journal of Financial Economics* 68, 413-437.

Easley, David, and Maureen O'Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics* 19, 69-90.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara, 2000, When the underwriter is the market maker: An examination of trading in the IPO aftermarket, *Journal of Finance* 55(3), 1039–1074.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams, 2008, Market madness? The case of mad money, *Working Paper*, University of North Carolina at Chapel Hill and Penn State University.

Fama, Eugene F., and James D. MacBeth, 1973, Risk Return and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607–636.

Fang, Lily, and Joel Peress, 2009, Media Coverage and the Cross-section of Stock Returns, *Journal of Finance* forthcoming.

Gervais, Simon, Ron Kaniel and Dan H. Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877–919.

Grullon, Gustavo, George Kanatas, and James P. Weston, 2004, Advertising, Breath of Ownership, and Liquidity, *Review of Financial Studies* 17, 439-461.

Hou, Kewei, Lin Peng and Wei Xiong, 2008, A tale of two anomalies: The implications of investor attention for price and earnings momentum, *Working Paper*, Ohio State University and Princeton University.

Ginsberg, Jeremy, Matthew H. Mohebbi, Rajan S. Patel, Lynnette Brammer, Mark S. Smolinski, and Larry Brilliant, 2009, Detecting influenza epidemics using search engine query data, *Nature* 457, 1012-1014.

Hanley, Kathleen Weiss, 1993, The underpricing of initial public offerings and the partial adjustment phenomenon, *Journal of Financial Economics* 34, 231-250.

Harris, Larry, 2003, *Trading and Exchanges: Market Microstructure for Practitioners*, Oxford University Press.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited Attention, Information Disclosure, and Financial Reporting, *Journal of Accounting and Economics* 36, 337-386.

Hvidkjaer, Soeren, 2008, Small Trades and the Cross-Section of Stock Returns, *Review of Financial Studies* 21(3), 1123-1151.

Ibbotson, Rorger, and Jeffrey F. Jaffe, 1975, 'Hot issue' markets, *Journal of Finance* 30, 10267 – 1042.

Kahneman, Daniel, 1973, *Attention and Effort*, Prentice-Hall, Englewood Cliffs, NJ.

Lee, Charles M. C. and Balkrishna Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets* 3(2), 83-111.

Liu, Laura, Ann E. Sherman, and Yong Zhang, 2009, the role of media in initial public offerings, *Working Paper*, DePaul University and Hong Kong University of Science and Technology.

Ljungqvist, Alexander, Vikram Nanda, and Raj Singh, 2006, Hot markets, investor sentiment, and IPO pricing, *Journal of Business* 79, 1667-1702.

Lou, Dong, 2008, Attracting Investor Attention through Advertising, *Working Paper*, Yale University.

Loughran, Tim and Jay Ritter, 1995, The New Issues Puzzle, *Journal of Finance* 50 (2), 23-51.

Loughran, Tim and Jay Ritter, 2002, Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs?, *Review of Financial Studies* 15 (2), 413-443.

Lowry, Michelle, and G. William Schwert, 2002, IPO market cycle: Bubbles or sequential learning?, *Journal of Finance* 57, 1171 –1200.

Merton, Robert C., 1987, A Simple Model of Capital Market Equilibrium with Incomplete Information, *Journal of Finance* 42 (3), 483-510.

Newey, Whitney and Kenneth West, 1987, A Simple Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica* 55, 703-708.

Ritter, Jay R., 1984, The 'hot issue' market of 1980, *The Journal of Business* 57, 215 – 240.

Ritter, Jay R., Ivo Welch, 2002, A Review of IPO Activity, Pricing, and Allocations, *Journal of Finance* 57(4), 1795-1828.

Seasholes, Mark S., and Guojun Wu, 2007, Predictable behavior, profits, and attention, *Journal of Empirical Finance* 14, 590 - 610.

Sims, Christopher A., 2003, Implications of Rational Inattention, *Journal of Monetary Economics* 50, 665-690.

Tetlock, Paul C., 2007, Giving Content to Investor Sentiment: The Role of Media in the Stock Market, *Journal of Finance* 62, 1139-1168.

Tetlock, Paul C., 2008, All the news that's fit to reprint: do investors react to stale information? *Working Paper*, Columbia University.

Tetlock, Paul C., 2009, Does Public Financial News Resolve Asymmetric Information? *Working Paper*, Columbia University.

Yuan, Yu, 2008, Attention and trading, *Working Paper*, University of Iowa.

Figure 1: Illustrations of Google Trends Search

Panel A represents the graphical output for a Google Trends' search of the terms "diet, cranberry." The graph plots weekly aggregate search frequency (SVI) for both "diet" and "cranberry." SVI for "diet" is the weekly search volume for "diet" scaled by the average search volume of "diet", while the SVI for "cranberry" is the weekly search volume for "cranberry" scaled by the average search volume of "diet." Panel B represents the graphical output for a Google Trends search of the terms "MSFT, AAPL." The graph plots weekly SVI for both "MSFT" and "AAPL." The SVI for "MSFT" is the weekly search volume for "MSFT" scaled by the average search volume of "MSFT" while the SVI for "AAPL" is the weekly search volume for "AAPL" scaled by the average search volume of "MSFT."

Panel A: Google Trends Search for "diet" and "cranberry".

Panel B: Google Trends Search for "MSFT, AAPL"

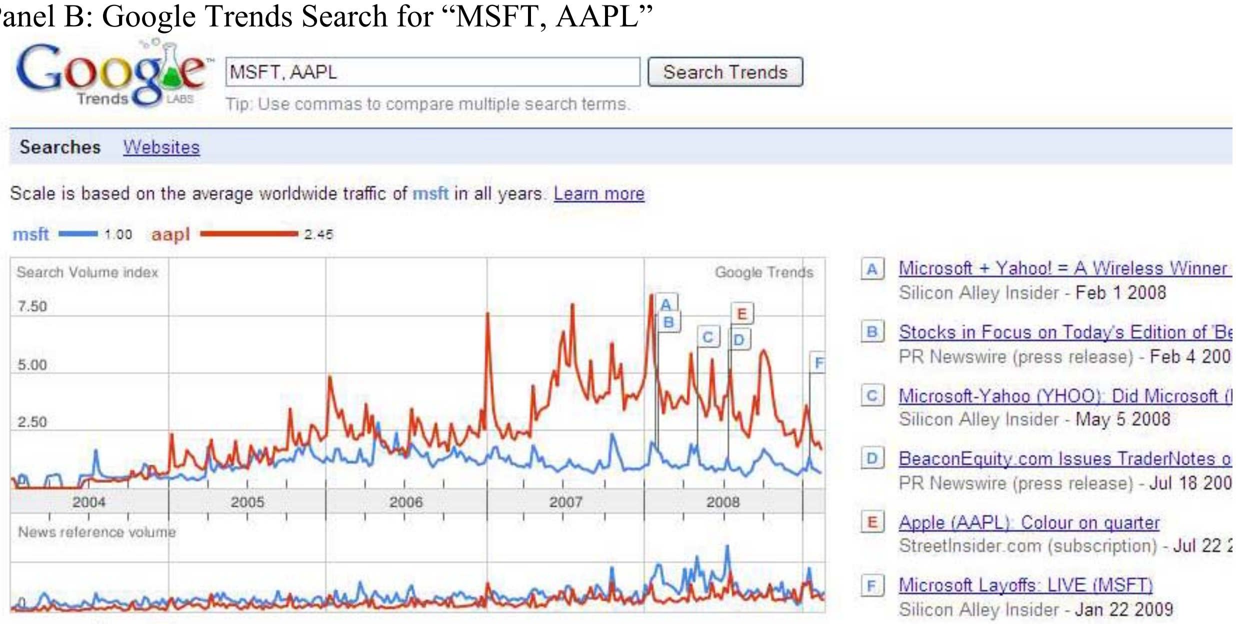
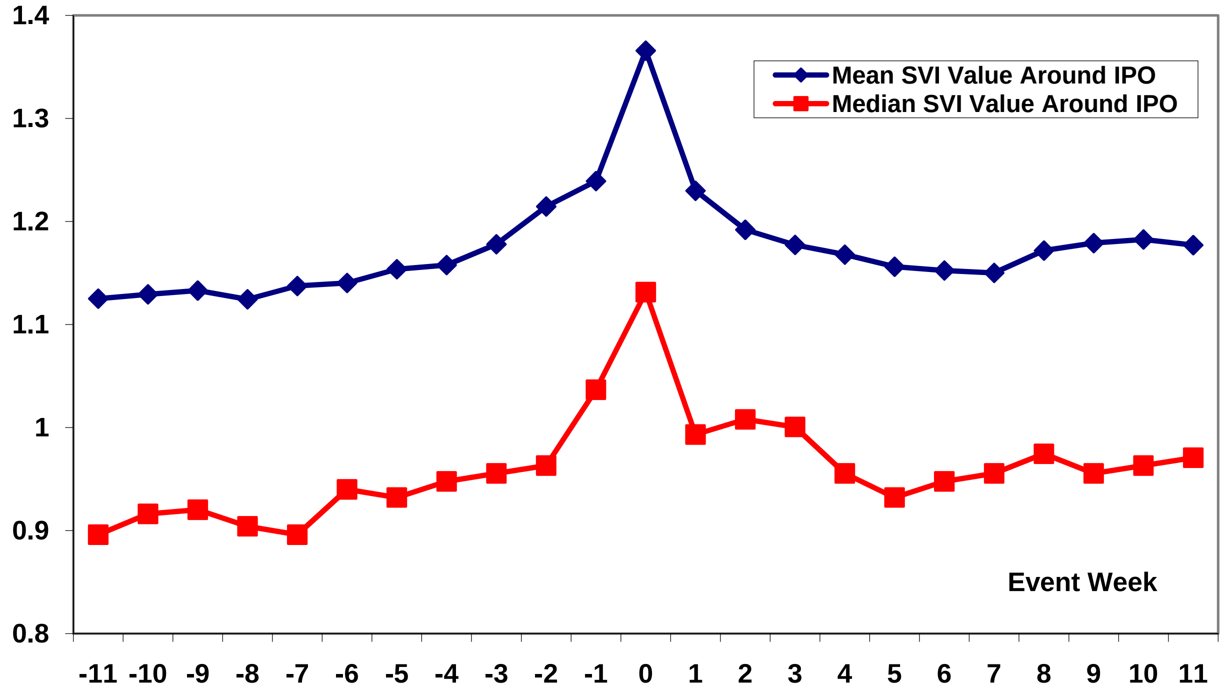


Figure 2: Average SVI and ASVI around IPO

Panel A plots the cross-sectional mean and median of the SVI (in logarithm) around the week of initial public offering (IPO). Panel B plots the cross-sectional mean and median of the Abnormal SVI (ASVI) around the week of IPO. Week 0 is the week of the IPO. The sample period is from January 2004 to December 2007. There are 185 IPOs with valid SVI in this sample.

Panel A: Cross-sectional Average Levels of SVI around IPO



Panel B: Cross-sectional Average Abnormal SVI (ASVI) around IPO

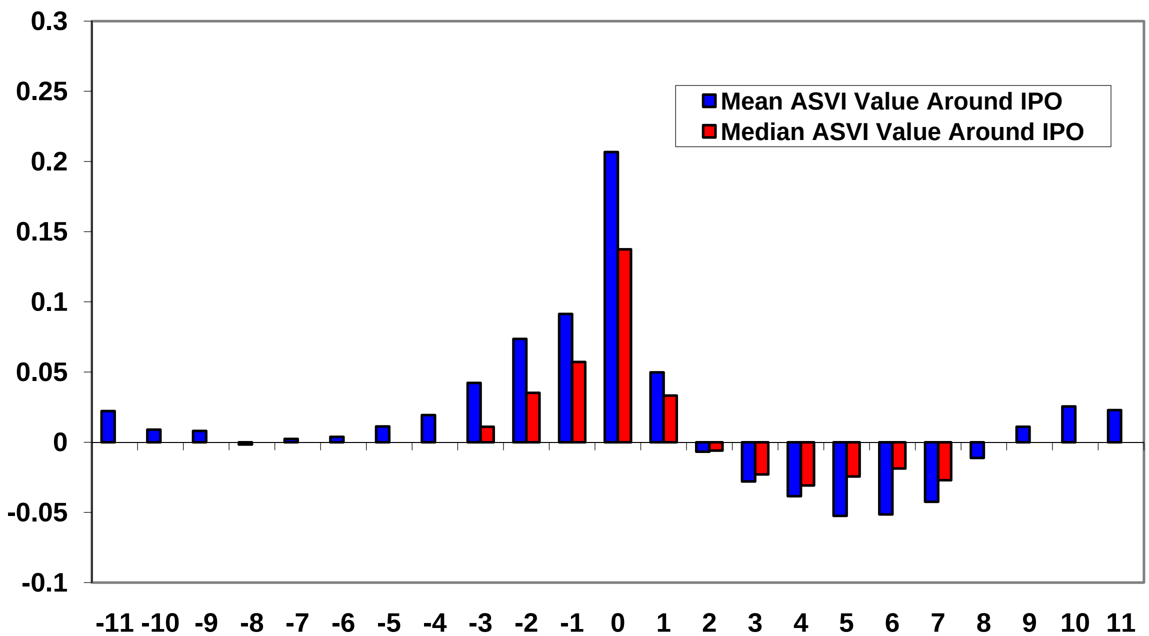
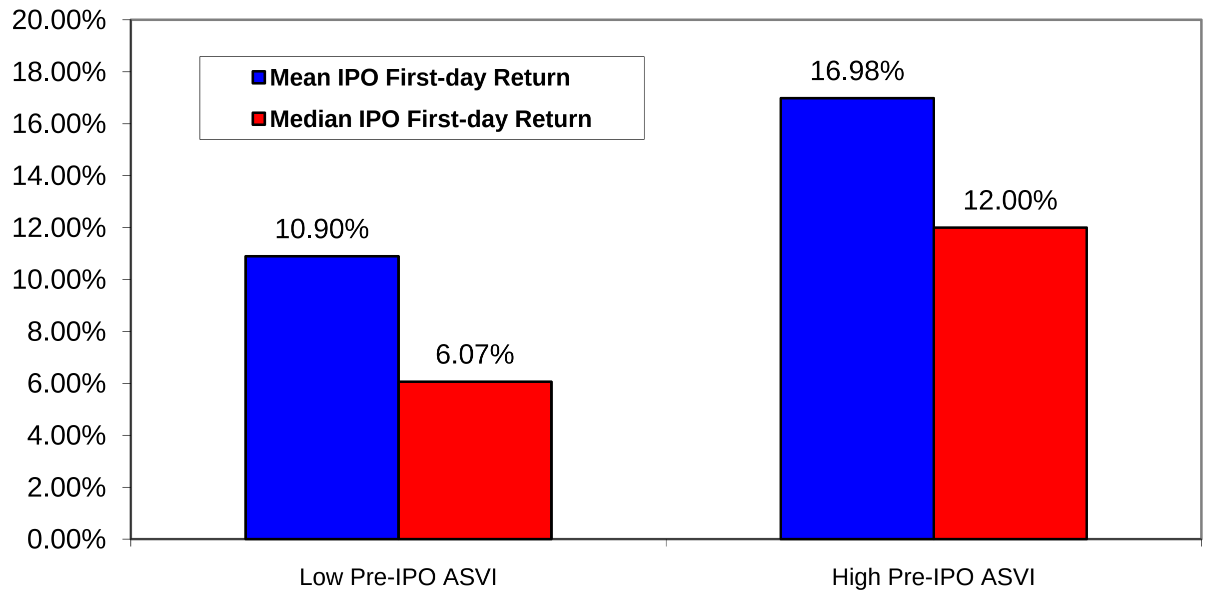


Figure 3: Pre-IPO ASVI, Average First-day IPO Returns and Long-Run IPO Returns

Panel A plots the pre-IPO ASVIs and average first-day returns. Panel B plots the pre-IPO ASVIs and the size and book to market equity matched portfolio adjusted cumulative abnormal returns from week 5 to week 52. The sample period is from January, 2004 to December, 2007. There are 185 IPOs with valid SVI in the sample.

Panel A: Pre-IPO ASVI and Average First-day IPO Returns



Panel B: Pre-IPO ASVIs and Cross-sectional Average of Industry-adjusted IPO Cumulative Returns (4 to 12 months)

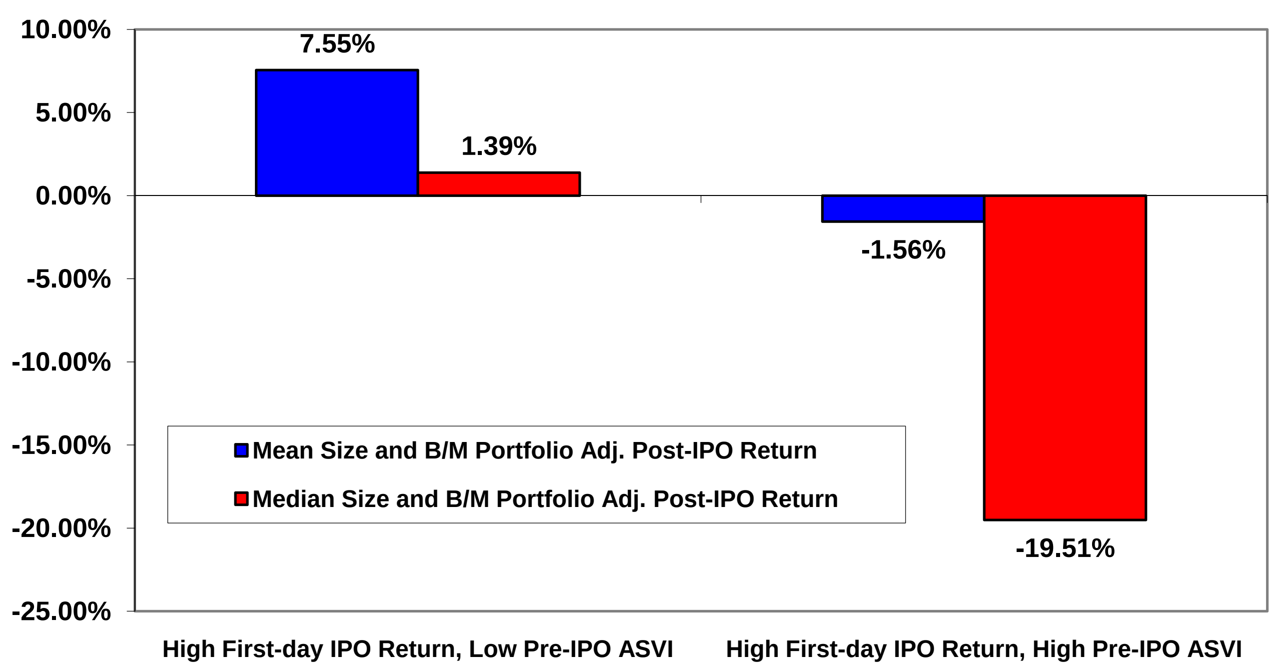


Table 1: Correlations

SVI is the aggregate search frequency from Google Trends based on stock ticker. Name_SVI is the aggregate search frequency based on company name. Absolute Abn Ret is the absolute value of the concurrent week DGTW abnormal return. Abnormal Turnover is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007); News refers to the number of news story in the Dow Jones news archive in the concurrent week. ChunkyNews refers to the number of news stories with multiple story codes in the Dow Jones news archive in the concurrent week. Following Tetlock (2007), we construct a media-based stock-level sentiment measure. For each stock each week, we gather all the news articles about the stock recorded in the Dow Jones Newswire (DJNW) database, and identify words with "negative sentiment". We count the total number of words of the entire collection of news articles about the stock (excluding so-called "stop words") within that week, and count the total number of "negative sentiment" words. Then we take the ratio of the number of "negative sentiment" words to the total number of words to get the fraction of negative words. Frac_Neg_H4 is the fraction when "negative sentiment" words are defined using the Harvard IV-4 dictionary and Frac_Neg_LM is the fraction following the word lists of Loughran and McDonald (2010). The sample period is from January 2004 to June 2008.

	log(SVI)	log(Name_SVI)	Absolute Abn Ret	Abnormal Turnover	log(1+News)	log(1+ ChunkyNews)	Frac_ Neg_H4	Frac_ Neg_LM
log(SVI)		0.093	0.069	0.045	0.065	0.045	0.026	0.017
log(Name_SVI)	0.093		0.092	0.108	0.157	0.157	0.041	0.020
Absolute Abn Ret	0.048	0.094		0.318	0.212	0.232	0.092	0.060
Abnormal Turnover	0.026	0.081	0.304		0.210	0.242	0.088	0.049
log(1+News)	0.034	0.151	0.186	0.153		0.643	0.278	0.119
log(1+ChunkyNews)	0.023	0.141	0.242	0.212	0.630		0.159	0.063
Frac_Neg_H4	0.020	0.086	0.126	0.127	0.488	0.356		0.695
Frac_Neg_LM	0.012	0.058	0.095	0.114	0.232	0.204	0.634	

Table 2: Vector Autoregression (VAR) Model of Attention Measures

We compare four weekly measures of attention using Vector Autoregressions (VARs). Log(SVI) is the natural logarithm of weekly aggregate search frequency (SVI); Log(Turnover) is the natural logarithm of weekly turnover; Absolute Abnormal return is the absolute value of the concurrent week DGTW abnormal return; and Log(1+Chunky News) is the natural logarithm of one plus the number of chunky news stories during the concurrent week. We run the VAR for each stock with at least two years of weekly data. We include both a constant and a time trend in the VAR. The VAR coefficients are then averaged across stocks and the associated p-values are reported below. These p-values are computed using a block bootstrap procedure under the null hypothesis that all VAR coefficients are zero. We start with the panel of residuals from the VAR and construct 10,000 bootstrapped panels. In the time series dimension, we block-bootstrap with replacement using a block length of 23 weeks to preserve autocorrelation structure in the error terms. In the cross-sectional dimension, we also bootstrap with replacement. We repeat the VAR estimation in each bootstrapped panel, which allows us to build up the empirical distributions of the VAR coefficients. *, ** and *** represent significance at the 10%, 5% and 1% level.

	Lagged One Week				
	log(SVI)	log(turnover)	Absolute Abnormal return	log(1+ Chunky News)	R2
log(SVI)	0.5646***	-0.0022***	0.0489***	-0.0027***	56.47%
	0.01	0.01	0.01	0.01	0.01
log(turnover)	0.0532**	0.4467***	0.5197***	-0.0298***	38.82%
	0.05	0.01	0.01	0.01	0.01
Absolute Abnormal return	0.0046***	0.0015***	0.0418***	-0.0011***	3.55%
	0.01	0.01	0.01	0.01	0.06
log(1+Chunky News)	0.0683**	0.0270***	0.2071**	0.0197***	3.19%
	0.02	0.01	0.05	0.01	0.01

Table 3: Abnormal SVI (ASVI) and Alternative Measures of Attention

The dependent variable in each regression is abnormal SVI defined as the log of SVI during the week minus the log of median SVI during the previous eight weeks. Log(Market Cap) is the natural logarithm of market capitalization. Absolute Abnormal return is the absolute value of the concurrent week DGTW abnormal return. Abnormal Turnover is the standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007). News Dummy is a dummy variable which takes the value 1 if there is a news story in the Dow Jones news archive in the concurrent week. Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive; Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S. Advertising Expense / Sales is the ratio between the advertising expense and sales in the previous fiscal year; and Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last fifty-two weeks. Robust standard errors clustered by firm are in parentheses. *, ** and *** represent significance at the 10%, 5% and 1% level. The sample period is from January 2004 to June 2008.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.099***	-0.096***	-0.095***	-0.096***	-0.096***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Log(Market Cap)	0.001**	0.000	0.000	0.000	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Abnormal return	0.131***	0.127***	0.127***	0.127***	0.129***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Abnormal Turnover	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
News Dummy	0.001				
	(0.001)				
Chunky News Dummy		0.004***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
Log(1+Number of Analysts)			0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)
Advertising Expense / Sales				0.007	0.010
				(0.011)	(0.011)
Log(Chunky News Last Year)					-0.001**
					(0.001)
Observations	411930	411930	411930	411930	411930
Week Fixed Effects	YES	YES	YES	YES	YES
Clusters (firms)	2435	2435	2435	2435	2435
R-Squared	0.03304	0.03315	0.03315	0.03315	0.03318

Table 4: Abnormal SVI (ASVI) and Individual Trading Reported by Dash-5

We measure individual trading using orders (market and marketable limit) and trades contained in SEC Rule 11Ac1-5 (Dash-5) reports. Panel A examines orders and trades reported by all market centers. We consider orders in two order size categories: (1) 100-1,999 shares and (2) 100-9,999 shares. Panel B considers orders in the 100-9,999 shares size category, examines different market centers separately (columns 1 through 4), and compares individual trading order / turnover response to concurrent SVI changes (column 5 and 6) using a paired sample design. Madoff (columns 1 and 2) refers to Madoff Security. NYSE/ARCH (columns 3 and 4) refer to New York Stock Exchange (for NYSE-listed stocks) and Archipelago Holdings (for NASDAQ-listed stocks).

In both panels, we regress monthly changes (log difference) in the number of individual orders (Δ Order) or monthly changes (log difference) in the individual turnover (Δ Turnover) on several variables. These include monthly SVI change, alternative measures of attention and other stock characteristics. SVI Change is the difference between the logarithm of SVI during month (t) and the logarithm of SVI during month (t-1), aggregated from weekly SVI. Among alternative measures of attention, Log(Market Cap) is the logarithm of the prior month-end (t-1) market capitalization; RET(t) is the monthly return from the current month (t); |RET(t)| is the absolute value of the return of the stock during month (t); Chunky News Dummy takes the value of one if there is at least one chunky news story in the Dow Jones News archive during month (t); Advert. Expense/Sales ratio is the latest advertisement expenditure to sales ratio available from Compustat prior to month (t), where we set advertisement expenditure equal to zero if advertisement expenditure is missing in COMPUSTAT. Control variables included several stock characteristics detailed in the paper. Finally, Madoff is a dummy variable taking a value of one for all observations from the Madoff market center and taking a value of zero for all observations from the New York Stock Exchange (for NYSE-listed stocks) and Archipelago Holdings (for NASDAQ-listed stocks).

All Regressions contain monthly fixed effects. Robust standard errors, reported in the parentheses, are clustered at the stock level. ***, **, and * denote the regression coefficient is statistically significant at the 1%, 5% and 10% level. The sample period is from January 2004 to June 2008.

Panel A: Regressions of monthly dash5 reported order and turnover changes by order sizes

	Order Size: 100 – 1999 shares		Order Size: 100 – 9999 shares	
	Δ Order	Δ Turnover	Δ Order	Δ Turnover
	(1)	(2)	(3)	(4)
ASVI (t-1, t)	0.0925***	0.0919***	0.103***	0.131***
	(0.0100)	(0.00915)	(0.0107)	(0.0118)
Log(Market Cap) (t-1)	-0.00670***	-0.00784***	-0.00757***	-0.0106***
	(0.000659)	(0.000645)	(0.000671)	(0.000759)
RET (t)	0.118***	0.122***	0.0989***	0.00722
	(0.0259)	(0.0241)	(0.0268)	(0.0293)
|RET(t)|	0.911***	1.023***	1.049***	1.503***
	(0.0486)	(0.0460)	(0.0500)	(0.0546)
Chunky News Dummy (t)	0.0874***	0.0942***	0.0924***	0.125***
	(0.00300)	(0.00285)	(0.00310)	(0.00326)
Advert. Expense / Sales (t)	-0.0429***	-0.0346***	-0.0506***	-0.0596***
	(0.0133)	(0.00977)	(0.0125)	(0.0112)
Constant	0.139***	0.145***	0.156***	0.179***
	(0.0155)	(0.0155)	(0.0158)	(0.0183)
Control Variables	YES	YES	YES	YES
Month Fixed Effect	YES	YES	YES	YES
Observations	108,954	108,954	108,954	108,954
Number of Clusters (Stock)	2,866	2,866	2,866	2,866
R-Squared	0.250	0.288	0.262	0.300

Panel B: Regressions of monthly dash5 reported order and turnover changes by market center

	Madoff		NYSE/ARCH		Comparison	
	Δ Order	Δ Turnover	Δ Order	Δ Turnover	Δ Order	Δ Turnover
	(1)	(2)	(3)	(4)	(5)	(6)
ASVI (t-1, t)	0.264***	0.297***	0.0920***	0.104***	0.166***	0.204***
	(0.0317)	(0.0355)	(0.0105)	(0.0132)	(0.0218)	(0.0256)
ASVI X Madoff					0.109***	0.0951**
					(0.0328)	(0.0374)
Madoff					0.000440	0.0223***
					(0.00223)	(0.00253)
Log(Market Cap) (t-1)	-0.0117***	-0.0122***	-0.00889***	-0.0129***	-0.00411***	-0.00841***
	(0.00202)	(0.00207)	(0.000641)	(0.000713)	(0.00132)	(0.00152)
RET (t)	0.154***	0.0772*	0.0999***	0.00647	0.0418	-0.0875***
	(0.0372)	(0.0437)	(0.0173)	(0.0199)	(0.0284)	(0.0331)
|RET(t)|	1.299***	1.570***	1.001***	1.418***	1.244***	1.622***
	(0.0528)	(0.0622)	(0.0271)	(0.0338)	(0.0405)	(0.0493)
Chunky News Dummy (t)	0.0658***	0.0915***	0.0936***	0.125***	0.0768***	0.0991***
	(0.00997)	(0.0121)	(0.00301)	(0.00364)	(0.00678)	(0.00841)
Advert. Expense / Sales (t)	-0.104*	-0.0954	0.00255	-0.0328***	-0.0713	-0.0568
	(0.0630)	(0.0642)	(0.00643)	(0.00636)	(0.0610)	(0.0658)
Constant	0.255***	0.251***	0.175***	0.229***	0.0570*	0.119***
	(0.0480)	(0.0492)	(0.0148)	(0.0167)	(0.0303)	(0.0349)
Control Variables	YES	YES	YES	YES	YES	YES
Month Fixed Effect	YES	YES	YES	YES	YES	YES
Observations	35,280	35,280	103,253	103,253	52,837	52,837
Number of Clusters (Stock)	1,358	1,358	2,743	2,743	962	962
R-Squared	0.131	0.127	0.299	0.291	0.173	0.191

Table 5: Abnormal SVI (ASVI) and Russell 3000 Stock Returns

This table reports the results from Fama-MacBeth (1973) cross-sectional regressions. The dependent variable is the DGTW abnormal return (in basis points) during the first four weeks and during week 5 to 52. ASVI is defined as the log of SVI during the week minus the log of median SVI during the previous eight weeks. Log(Market Cap) is the natural logarithm of market capitalization. Percent Dash-5 Volume is defined as the ratio between Dash-5 trading volume and the total trading volume during the previous month. APSVI is log of PSVI (product SVI) during the week minus the log of median PSVI during the previous eight weeks. Absolute Abnormal return is the absolute value of the concurrent week DGTW abnormal return. Advertising Expense / Sales is the ratio between the advertising expense and sales in the previous fiscal year. Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S. Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last fifty-two weeks. Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive. Abnormal Turnover is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007). All variables are cross-sectionally demeaned (so the regression intercept is zero) and independent variables are also standardized (so the regression coefficients can be interpreted as the impact of a one standard deviation change). Standard errors are computed using the Newey-West (1985) formula with 8 lags. *, ** and *** represent significance at the 10%, 5% and 1% level. The sample period is from January 2004 to June 2008.

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5-52 (5)
ASVI	18.742***	14.904**	3.850	-1.608	-28.912
	(7.000)	(7.561)	(6.284)	(6.903)	(17.162)
Log Market Cap * ASVI	-21.182***	-15.647**	-4.710	4.290	16.834
	(6.508)	(6.768)	(6.516)	(6.398)	(88.624)
Log Market Cap	2.653	3.858	3.144	3.575	-39.229
	(3.023)	(3.160)	(3.063)	(3.186)	(67.405)
Percent Dash-5 Volume * ASVI	3.552**	1.904	1.687	-2.744	16.258
	(1.639)	(1.522)	(1.612)	(1.717)	(23.822)
Percent Dash-5 Volume	1.607	1.351	1.486	0.364	119.901***
	(1.644)	(1.652)	(1.659)	(1.711)	(31.765)
APSVI	-2.532***	-1.379	-0.701	-0.704	2.286
	(0.930)	(0.990)	(0.808)	(0.639)	(9.909)
Absolute Abnormal Return	1.314	-2.389	-1.128	-0.463	-1.510
	(1.879)	(1.979)	(1.563)	(1.405)	(28.505)
Advertising Expense / Sales	-4.012*	-4.686**	-3.959*	-4.153*	-162.210***
	(2.237)	(2.228)	(2.172)	(2.234)	(52.414)
Log(1 + # of analysts)	-3.747**	-4.547***	-3.961**	-4.120**	-173.875***
	(1.548)	(1.741)	(1.769)	(1.769)	(29.683)
Log(Chunky News Last Year)	-5.157	-5.549*	-4.349	-5.409	-14.999
	(3.370)	(3.272)	(3.292)	(3.558)	(80.730)
Chunky News Dummy	3.610*	1.378	-3.825	-0.058	32.466
	(2.025)	(2.424)	(2.483)	(1.910)	(28.441)
Abnormal Turnover	2.398**	2.309**	2.022	0.316	10.531
	(1.204)	(1.144)	(1.404)	(1.098)	(10.109)
Observations per week	1499	1498	1497	1496	1414
R-Squared	0.0142	0.0119	0.0112	0.0111	0.0170

Table 6: Abnormal SVI (ASVI) and Russell 3000 Stock Returns: Robustness

We repeat the analysis in Table 7 in several subsamples. Panel A reports the regression results for the sampling period from January 2004 to May 2006 and Panel B reports the regression results for the sampling period from June 2006 to June 2008. Panel C reports the regression results after we exclude "noisy" tickers from our sample.

Panel A: Jan 2004 to Jun 2006

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5-52 (5)
ASVI	20.061**	2.569	4.401	-10.314	-5.037
	(9.774)	(7.730)	(8.137)	(9.289)	(13.600)
Log Market Cap * ASVI	-19.532**	-5.402	-6.347	11.980	-65.282
	(8.771)	(6.854)	(8.000)	(8.321)	(141.800)
Log Market Cap	-1.541	-0.473	-1.421	-1.586	-261.431***
	(2.969)	(2.615)	(2.701)	(2.745)	(60.599)
Percent Dash-5 Volume * ASVI	0.490	3.199*	2.462	-1.779	23.025
	(2.270)	(1.895)	(2.101)	(2.334)	(34.531)
Percent Dash-5 Volume	4.010**	3.388*	3.496**	2.991	210.549***
	(2.008)	(2.033)	(1.708)	(1.975)	(28.601)
APSVI	-2.429***	-0.425	-0.219	-0.467	0.835
	(0.919)	(1.114)	(0.807)	(0.668)	(13.663)
Absolute Abnormal Return	3.298	-0.547	-0.677	0.571	75.716**
	(2.594)	(2.637)	(2.335)	(1.822)	(33.768)
Advertising Expense / Sales	-2.447	-3.781	-2.812	-3.831	-97.427*
	(2.336)	(2.543)	(2.411)	(2.608)	(52.064)
Log(1 + # of analysts)	-4.548**	-5.004**	-5.001*	-4.272*	-273.977***
	(2.164)	(2.426)	(2.640)	(2.436)	(29.380)
Chunky News last year	0.702	-0.175	0.730	0.826	277.982***
	(3.286)	(3.054)	(2.950)	(3.294)	(46.990)
This Week Chunky News Dummy	3.252	2.141	-2.248	-2.128	57.719
	(2.792)	(2.943)	(2.977)	(2.333)	(47.286)
Abnormal Turnover	1.490	1.112	2.755	0.101	-0.340
	(1.615)	(1.321)	(1.764)	(1.394)	(15.244)
Observations per week	1381	1381	1380	1379	1314
R-Squared	0.0128	0.0112	0.0106	0.0102	0.0146

Panel B: Jul 2006 to Jun 2008

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5-52 (5)
ASVI	17.105*	30.205**	3.166	9.191	-58.280*
	(10.078)	-12.676	-9.711	(9.701)	(31.307)
Log Market Cap * ASVI	-23.228**	-28.354**	-2.679	-5.247	118.689
	(9.747)	-11.551	-10.536	(9.206)	(83.997)
Log Market Cap	7.855	9.23	8.806	9.978*	236.388***
	(5.416)	-6.001	-5.599	(5.795)	(71.393)
Percent Dash-5 Volume * ASVI	7.350***	0.297	0.726	-3.941*	7.866
	(1.781)	-2.424	-2.437	(2.363)	(31.890)
Percent Dash-5 Volume	-1.374	-1.175	-1.008	-2.894	7.464
	(2.472)	-2.627	-2.912	(2.673)	(44.387)
APSVI	-2.659	-2.561	-1.299	-0.997	4.085
	(1.762)	-1.682	-1.496	(1.147)	(14.350)
Absolute Abnormal Return	-1.146	-4.675	-1.687	-1.746	-97.299***
	(2.568)	-2.89	-2.062	(2.133)	(30.398)
Advertising Expense / Sales	-5.954	-5.809	-5.381	-4.551	-242.567**
	(4.010)	-3.92	-3.769	(3.789)	(93.262)
Log(1 + # of analysts)	-2.753	-3.98	-2.671	-3.931	-49.711*
	(2.223)	-2.502	-2.455	(2.592)	(27.829)
Chunky News last year	-12.424**	-12.215**	-10.650*	-13.143**	-378.407***
	(5.776)	-5.779	-5.932	(6.144)	(89.219)
This Week Chunky News Dummy	4.054	0.432	-5.781	2.509	1.142
	(2.994)	-3.904	-4.038	(2.988)	(22.158)
Abnormal Turnover	3.524**	3.794**	1.112	0.584	24.016**
	(1.771)	-1.836	-2.25	(1.783)	(11.769)
Observations per week	1645	1644	1643	1641	1538
R-Squared	0.0160	0.0128	0.0118	0.0122	0.0199

Panel C: Excluding Noisy Tickers

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5-52 (5)
ASVI	19.294**	16.593*	-0.616	-5.594	-27.370
	(8.299)	(8.472)	(7.447)	(7.427)	(19.438)
Log Market Cap * ASVI	-21.765***	-16.724**	-0.257	8.532	12.332
	(7.983)	(7.357)	(7.561)	(7.020)	(77.423)
Log Market Cap	3.454	4.706	3.894	3.445	12.457
	(2.990)	(3.074)	(2.940)	(3.076)	(56.531)
Percent Dash-5 Volume * ASVI	3.425*	1.307	1.173	-3.287*	18.029
	(1.772)	(1.796)	(1.934)	(1.861)	(22.801)
Percent Dash-5 Volume	1.115	0.706	0.801	-0.241	76.824***
	(1.682)	(1.695)	(1.746)	(1.801)	(28.358)
APSVI	-1.959**	-0.808	0.264	0.305	1.226
	(0.887)	(0.962)	(0.868)	(0.758)	(10.289)
Absolute Abnormal Return	2.054	-3.029	-0.894	-1.199	-21.743
	(2.179)	(2.199)	(1.749)	(1.566)	(24.176)
Advertising Expense / Sales	-6.354**	-7.000**	-6.265**	-5.871**	-297.247***
	(2.946)	(2.939)	(2.781)	(2.791)	(70.240)
Log(1 + # of analysts)	-4.240***	-5.107***	-4.364**	-4.178**	-180.197***
	(1.586)	(1.824)	(1.810)	(1.749)	(32.032)
Chunky News last year	-5.760	-5.922*	-4.785	-5.402	-11.125
	(3.564)	(3.355)	(3.310)	(3.643)	(76.974)
This Week Chunky News Dummy	3.121	0.452	-4.264	-0.872	13.914
	(2.118)	(2.669)	(2.597)	(2.157)	(27.867)
Abnormal Turnover	2.088	2.781**	3.089**	0.344	23.410**
	(1.355)	(1.237)	(1.436)	(1.293)	(10.459)
Observations per week	1187	1187	1186	1185	1122
R-Squared	0.0152	0.0123	0.0119	0.0113	0.0167

Table 7: Pre-IPO Abnormal Search Volume (ASVI) and IPO First-day Return

This table regresses IPO first-day return on the pre-IPO week abnormal search volume (ASVI) and IPO characteristics. The dependent variable is the individual IPO's first-day return, computed as the first CRSP available closing price divided by the offering price minus one. *ASVI* is defined as the log of SVI during the week prior to the IPO week (w-1) minus the log of the median SVI (w-9, w-2), where w is the week the company went public. *Media* is the logarithm of the number of news articles recorded by the Factiva (using company name as the search criteria) between filing date (inclusive) and IPO date (exclusive), normalized by the days between filing day and IPO day. *Price Revision* is the ratio of the offering price divided by the medium of the filing price. *DSENT* is the Baker-Wurgler monthly investor sentiment change (orthogonal to macro variables) at the month when the firm goes to public, obtained from Jeffery Wurgler's website. *Log(Offering Size)* is the logarithm of offering size, where the offering size is defined as the offering price multiplied by the number of shares offered. Log(Age) is the logarithm of years between the firm's founding year and the year of IPO, where the firm age is obtained from Jay Ritter's website and supplemented by hand-collected information from various sources. *Log(Asset Size)* is the logarithm of firm's total assets prior to IPO. *CM Underwriter Ranking* is the Carter-Manaster ranking of lead underwriter, obtained from Jay Ritter's website. *VC Backing* is a binary indicator variable taking a value of one if the IPO is backed by a venture capital firm, and zero otherwise. *Secondary Share Overhang* is defined as secondary shares offered / (IPO share offered + secondary share offered). *Past Industry Return* is the Fama-French 48-industry portfolio return corresponding to the industry classification of the IPO at the time of public offering. The Sample period of IPOs is from 2004 to 2007. Only regular and common stock IPOs (CRSP share class in 10 and 11) traded on NYSE, AMEX and NASDAQ with valid SVI (searched using company names) are retained in the sample. Only the IPOs with the first available CRSP close price less than or equal to five days from the IPO date are retained. The standard errors (in parentheses) are clustered by the offering year and quarter. *, ** and *** denote the regression coefficients are statistically significant at the 10%, 5% and 1% level respectively.

	Dependent Variable: IPO First-day Return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ASVI	0.275**				0.203**				0.189**
	(0.101)				(0.0795)				(0.0705)
Media		0.0292*				0.0255**			0.0246
		(0.0149)				(0.0114)			(0.0144)
Price Revision			0.460***				0.358***		0.350***
			(0.0806)				(0.0989)		(0.101)
DSENT				0.0134				0.0194*	0.0221*
				(0.0119)				(0.00933)	(0.0104)
Log(Offering Size)					0.0805***	0.0724***	0.0344	0.0855***	0.0168
					(0.0130)	(0.0128)	(0.0219)	(0.0150)	(0.0177)
Log(Age)					0.0187	0.00995	0.0131	0.0131	0.0121
					(0.0167)	(0.0149)	(0.0165)	(0.0164)	(0.0113)
Log(Asset Size)					-0.0452***	-0.0446***	-0.0239***	-0.0453***	-0.0197**
					(0.00987)	(0.00963)	(0.00799)	(0.00940)	(0.00692)
CM Underwriter Ranking					-0.00331	-0.000222	0.00670	-0.000851	0.00531
					(0.00367)	(0.00319)	(0.00453)	(0.00382)	(0.00406)
VC Backing					0.0430	0.0468	0.0555*	0.0463	0.0576*
					(0.0289)	(0.0313)	(0.0270)	(0.0311)	(0.0286)
Secondary Share Overhang					-0.0330	-0.0332	-0.0221	-0.0308	-0.0345
					(0.0245)	(0.0203)	(0.0218)	(0.0222)	(0.0216)
Past Industry Return					0.199**	0.259***	0.128	0.227***	0.185**
					(0.0904)	(0.0744)	(0.102)	(0.0765)	(0.0866)
Constant	0.114***	0.0539	0.143***	0.135***	-0.747***	-0.713***	-0.301	-0.811***	-0.180
	(0.0146)	(0.0409)	(0.0125)	(0.0126)	(0.185)	(0.179)	(0.271)	(0.209)	(0.221)
Observations	185	185	185	185	185	185	185	185	185
R-Squared	0.052	0.037	0.235	-0.001	0.217	0.214	0.288	0.194	0.340

Table 8: Pre-IPO Abnormal Search Volume (ASVI) and Post-IPO Performance

This table considers the cumulative IPO raw return (Panel A), cumulative IPO return adjusted by cumulative industry returns (Panel B), and cumulative IPO return adjusted by cumulative size and book to market equity matched portfolio (excluding stocks issued in the past five years) returns (Panel C) during the fourth to the twelfth month after the initial public offering. The dependent variable in Panel A is the individual IPO's cumulative return during the [w+5, w+52] week window after the initial public offering, where the week w is the week when the company went to public. The dependent variable in Panel B is the individual IPO's cumulative return during the [w+5, w+52] week window after the initial public offering adjusted by the corresponding industry matched portfolio returns during the same event window. The dependent variable in Panel C is the individual IPO's cumulative return during the [w+5, w+52] week window after the initial public offering adjusted by the corresponding size and book to market equity matched portfolio (excluding recent IPO stocks in the past five years) returns during the same event window. To generate the size and book to market equity matched portfolio returns of non-IPOs, we first match the first available market capitalization of the IPO with the immediate past June's NYSE market capitalization quintile breakpoint, then match with IPO's book to market equity ratio with the portfolio of stocks of the closest book to market equity quintile within the matched size quintile. Thus, the IPO is matched with one of the 25 size and book to market equity double sorted portfolios of non-IPO stocks. The book-value of IPO is the first available book value of equity immediately after IPO, and the market equity is the first available market capitalization of IPO. The *First-day Return* is computed as the first CRSP available closing price divided by the offering price minus one. *ASVI* is defined as the log of SVI during the week prior to the IPO week (w-1) minus the log of the median SVI (w-9, w-2), where w is the week the company went public. *Media* is the logarithm of the number of news articles recorded by the Factiva (using company name as the search criteria) between filing date (inclusive) and IPO date (exclusive), normalized by the days between filing day and IPO day. *Price Revision* is the ratio of the offering price divided by the medium of the filing price. *DSENT* is the Baker-Wurgler monthly investor sentiment change (orthogonal to macro variables) at the month when firm goes to public, obtained from Jeffery Wurgler's website. *Log(Offering Size)* is the logarithm of offering size, where the offering size is defined as the offering price multiplied by the number of shares offered. Log(Age) is the logarithm of years between firm's founding year and the year of IPO, where the firm age is obtained from Jay Ritter's website and supplemented by hand-collected information from various sources. *Log(Asset Size)* is the logarithm of firm's total assets prior to IPO. *CM Underwriter Ranking* is the Carter-Manaster ranking of lead underwriter, obtained from Jay Ritter's website. *VC Backing* is a binary indicator variable taking value of one if the IPO is backed by a venture capital firm, and zero otherwise. *Secondary Share Overhang* is defined as the secondary shares offered / (IPO share offered + secondary share offered). *Past Industry Return* is the Fama-French 48-industry portfolio return corresponding to the industry classification of the IPO at the time of public offering. The Sample period of IPOs is from 2004 to 2007. Only regular and common stock IPOs (CRSP share class in 10 and 11) traded on NYSE, AMEX and NASDAQ with valid SVI (searched using company names) are retained in the sample. Only the IPOs with the first available CRSP close price less than or equal to five days from the IPO date are retained. The standard errors (in parentheses) are clustered by the offering year and quarter. *, ** and *** denote the regression coefficients are statistically significant at the 10%, 5% and 1% level respectively.

Panel A: Pre-IPO Abnormal Search Volume (ASVI) and IPO Returns

	Dependent Variable: IPO Return					
	(1)	(2)	(3)	(4)	(5)	(6)
ASVI	-0.176	0.499	-0.182	-0.167	-0.176	0.546
	(0.244)	(0.442)	(0.239)	(0.248)	(0.246)	(0.510)
ASVI x First-day Return		-3.065**				-3.330**
		(1.069)				(1.438)
Media	0.0523	0.0413	0.0611	0.0565	0.0521	0.0583
	(0.0421)	(0.0451)	(0.0437)	(0.0427)	(0.0417)	(0.0441)
Media x First-day Return			-0.0413			-0.0851
			(0.0441)			(0.0792)
Price Revision	-0.0421	0.0396	-0.0382	-0.0422	-0.0420	0.0554
	(0.181)	(0.184)	(0.186)	(0.179)	(0.182)	(0.193)
Price Revision x First-day Return				-0.434		-0.144
				(0.375)		(0.520)
DSENT	-0.0646	-0.0501	-0.0621	-0.0656	-0.0664	-0.0573
	(0.0606)	(0.0645)	(0.0622)	(0.0616)	(0.0701)	(0.0743)
DSENT x First-day Return					0.0154	0.112
					(0.183)	(0.247)
First-day Return	-0.110	0.173	0.00330	-0.0323	-0.117	0.404
	(0.176)	(0.235)	(0.135)	(0.228)	(0.227)	(0.255)
Log(Offering Size)	0.0411	0.0382	0.0423	0.0438	0.0411	0.0413
	(0.130)	(0.132)	(0.132)	(0.129)	(0.130)	(0.136)
Log(Age)	-0.0184	-0.0217	-0.0146	-0.0227	-0.0184	-0.0157
	(0.0667)	(0.0681)	(0.0635)	(0.0662)	(0.0672)	(0.0616)
Log(Asset Size)	-0.0159	-0.0184	-0.0155	-0.0143	-0.0161	-0.0181
	(0.0568)	(0.0593)	(0.0568)	(0.0580)	(0.0570)	(0.0618)
CM Underwriter Ranking	0.0279	0.0267	0.0269	0.0279	0.0279	0.0243
	(0.0221)	(0.0230)	(0.0223)	(0.0224)	(0.0222)	(0.0235)
VC Backing	-0.170	-0.186	-0.170	-0.168	-0.170	-0.183
	(0.174)	(0.171)	(0.175)	(0.176)	(0.175)	(0.176)
Secondary Share Overhang	-0.179	-0.187	-0.178	-0.176	-0.179	-0.185
	(0.104)	(0.116)	(0.102)	(0.104)	(0.104)	(0.116)
Past Industry Return	-0.425	-0.379	-0.417	-0.425	-0.425	-0.357
	(0.297)	(0.292)	(0.294)	(0.297)	(0.297)	(0.286)
Constant	-0.399	-0.343	-0.448	-0.450	-0.397	-0.439
	(1.164)	(1.156)	(1.235)	(1.154)	(1.163)	(1.245)
Observations	185	185	185	185	185	185
R-Squared	0.002	0.011	0.003	0.003	0.004	0.003

Panel B: Pre-IPO Abnormal Search Volume (ASVI) and Industry Matched Portfolio Adjusted IPO Returns

	Dependent Variable: Industry Matched Portfolio Adjusted IPO Return					
	(1)	(2)	(3)	(4)	(5)	(6)
ASVI	-0.192	0.359	-0.188	-0.186	-0.194	0.349
	(0.155)	(0.307)	(0.157)	(0.157)	(0.155)	(0.349)
ASVI x First-day Return		-2.501***				-2.456**
		(0.834)				(1.038)
Media	0.0176	0.00861	0.0107	0.0207	0.0152	0.00990
	(0.0328)	(0.0340)	(0.0347)	(0.0335)	(0.0325)	(0.0345)
Media x First-day Return			0.0321			-0.00863
			(0.0509)			(0.0690)
Price Revision	-0.0607	0.00603	-0.0637	-0.0607	-0.0597	0.00666
	(0.174)	(0.185)	(0.173)	(0.174)	(0.175)	(0.189)
Price Revision x First-day Return				-0.326		-0.198
				(0.365)		(0.468)
DSENT	-0.0612	-0.0494	-0.0632	-0.0620	-0.0802	-0.0705
	(0.0446)	(0.0473)	(0.0462)	(0.0456)	(0.0563)	(0.0602)
DSENT x First-day Return					0.160	0.176
					(0.163)	(0.167)
First-day Return	0.0143	0.245	-0.0738	0.0727	-0.0621	0.216
	(0.173)	(0.188)	(0.178)	(0.223)	(0.206)	(0.229)
Log(Offering Size)	0.0609	0.0586	0.0600	0.0629	0.0609	0.0601
	(0.101)	(0.103)	(0.102)	(0.100)	(0.101)	(0.102)
Log(Age)	-0.0255	-0.0282	-0.0284	-0.0287	-0.0257	-0.0296
	(0.0442)	(0.0451)	(0.0443)	(0.0446)	(0.0450)	(0.0444)
Log(Asset Size)	-0.0243	-0.0262	-0.0246	-0.0230	-0.0256	-0.0268
	(0.0386)	(0.0394)	(0.0383)	(0.0397)	(0.0378)	(0.0401)
CM Underwriter Ranking	0.0114	0.0104	0.0122	0.0114	0.0112	0.0100
	(0.0161)	(0.0168)	(0.0164)	(0.0162)	(0.0163)	(0.0174)
VC Backing	-0.153	-0.166	-0.153	-0.152	-0.148	-0.159
	(0.126)	(0.122)	(0.126)	(0.128)	(0.129)	(0.127)
Secondary Share Overhang	-0.108	-0.114	-0.109	-0.106	-0.110	-0.115
	(0.0792)	(0.0866)	(0.0797)	(0.0789)	(0.0800)	(0.0869)
Past Industry Return	-0.402*	-0.364	-0.408*	-0.402*	-0.401*	-0.361
	(0.217)	(0.217)	(0.220)	(0.215)	(0.222)	(0.215)
Constant	-0.508	-0.462	-0.470	-0.546	-0.486	-0.471
	(1.013)	(1.009)	(1.040)	(0.994)	(1.006)	(1.030)
Observations	185	185	185	185	185	185
R-Squared	0.010	0.001	0.015	0.015	0.013	0.015

Panel C: Pre-IPO Abnormal Search Volume (ASVI) and Book to Market Equity/ Size Matched Portfolio Adjusted IPO Return

	Dependent Variable: Size and B/M Matched Portfolio Adjusted IPO Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
ASVI	-0.226	0.252	-0.226	-0.219	-0.227	0.263
	(0.173)	(0.363)	(0.173)	(0.174)	(0.174)	(0.408)
ASVI x First-day Return		-2.169**				-2.239*
		(1.013)				(1.244)
Media	0.0394	0.0316	0.0394	0.0425	0.0371	0.0392
	(0.0389)	(0.0412)	(0.0397)	(0.0401)	(0.0388)	(0.0406)
Media x First-day Return			8.40e-05			-0.0416
			(0.0525)			(0.0656)
Price Revision	-0.0180	0.0398	-0.0180	-0.0181	-0.0171	0.0468
	(0.185)	(0.199)	(0.186)	(0.187)	(0.185)	(0.205)
Price Revision x First-day Return				-0.326		-0.217
				(0.420)		(0.566)
DSENT	-0.0366	-0.0264	-0.0366	-0.0374	-0.0551	-0.0491
	(0.0426)	(0.0453)	(0.0447)	(0.0434)	(0.0572)	(0.0619)
DSENT x First-day Return					0.156	0.211
					(0.179)	(0.169)
First-day Return	-0.116	0.0849	-0.116	-0.0572	-0.190	0.144
	(0.193)	(0.211)	(0.176)	(0.255)	(0.202)	(0.224)
Log(Offering Size)	0.0447	0.0427	0.0447	0.0467	0.0447	0.0452
	(0.108)	(0.109)	(0.109)	(0.107)	(0.107)	(0.109)
Log(Age)	-0.0386	-0.0410	-0.0386	-0.0419	-0.0389	-0.0397
	(0.0421)	(0.0424)	(0.0421)	(0.0432)	(0.0427)	(0.0432)
Log(Asset Size)	-0.0338	-0.0355	-0.0338	-0.0326	-0.0351	-0.0361
	(0.0416)	(0.0419)	(0.0414)	(0.0425)	(0.0404)	(0.0424)
CM Underwriter Ranking	0.0166	0.0158	0.0166	0.0167	0.0165	0.0145
	(0.0191)	(0.0197)	(0.0195)	(0.0192)	(0.0193)	(0.0203)
VC Backing	-0.153	-0.164	-0.153	-0.152	-0.148	-0.157
	(0.125)	(0.121)	(0.125)	(0.126)	(0.128)	(0.127)
Secondary Share Overhang	-0.137	-0.142	-0.137	-0.135	-0.139	-0.143
	(0.0904)	(0.0965)	(0.0902)	(0.0901)	(0.0908)	(0.0961)
Past Industry Return	-0.276	-0.243	-0.276	-0.276	-0.275	-0.232
	(0.250)	(0.253)	(0.248)	(0.247)	(0.254)	(0.243)
Constant	-0.267	-0.227	-0.267	-0.305	-0.245	-0.270
	(1.066)	(1.069)	(1.114)	(1.045)	(1.063)	(1.096)
Observations	185	185	185	185	185	185
R-Squared	0.011	0.005	0.017	0.016	0.015	0.020