In Search of Attention

Author(s): ZHI DA, JOSEPH ENGELBERG and PENGJIE GAO

Source: *The Journal of Finance*, OCTOBER 2011, Vol. 66, No. 5 (OCTOBER 2011), pp. 1461-1499

Published by: Wiley for the American Finance Association

Stable URL: https://www.jstor.org/stable/41305167

THE JOURNAL OF FINANCE • VOL. LXVI, NO. 5 • OCTOBER 2011

In Search of Attention

ZHI DA, JOSEPH ENGELBERG, and PENGJIE GAO*

ABSTRACT

We propose a new and direct measure of investor attention using search frequency in Google (Search Volume Index (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 2 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.

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. "Designing Organizations for an Information-Rich World," in Martin Greenberger, Computers, Communication, and the Public Interest *[Baltimore, MD: The Johns Hopkins Press, 1971, 40–41]*

Herbert Simon, Nobel Laureate in Economics

TRADITIONAL ASSET PRICING models assume that information is instantaneously incorporated into prices when it arrives. This assumption requires that

*Da is with University of Notre Dame, Engelberg is with the University of California at San Diego, and Gao is with University of Notre Dame. We thank Nick Barberis; Robert Battalio; Andriy Bodnaruk; Zhiwu Chen; Jennifer Conrad; Shane Corwin; Mark Greenblatt; Campbell Harvey (the editor); David Hirshleifer; Kewei Hou; Byoung-Hyoun Hwang; Ryan Israelsen; Ravi Jagannathan; Robert Jennings; Gabriele Lepori; Dong Lou; Tim Loughran; Ernst Schaumburg; Paul Schultz; Mark Seasholes; Ann Sherman; Sophie Shive; Avanidhar Subrahmanyam; Paul Tetlock; Heather Tookes; Annette Vissing-Jorgensen; Mitch Warachka; Yu Yuan; an anonymous associate editor; two anonymous referees; and seminar participants at AQR Capital Management, HEC Montreal, Purdue University, Singapore Management University, University of California at Irvine, University of North Carolina at Chapel Hill, University of Georgia, University of Hong Kong, University of Oklahoma, University of Notre Dame, Fifth Yale Behavioral Science Conference, the 2009 NBER Market Microstructure meeting, Macquarie Global Quant Conference, 2009 Chicago Quantitative Aliance Academic Competition, 2010 American Finance Association, 2010 Crowell Memorial Prize Paper Competition, and Center of Policy and Economic Research (CEPR) European Summer Symposia for helpful comments and discussions. We thank Frank Russell and Company for providing us with the historical Russell 3000 index membership data, Dow Jones & Company for providing us with the news data, Market System Incorporated (MSI) for providing us with the Dash-5 data, and IPO SCOOP for providing us with the IPO rating data. We are grateful to Robert Battalio, Hyunyoung Choi, Amy Davison, Ann Sherman, and Paul Tetlock for their assistance with some of the data used in this study. Xian Cai, Mei Zhao, Jianfeng Zhu, and Mendoza IT Group provided superb resesearch assistance. We are responsible for remaining errors.

investors allocate sufficient attention to the asset. In reality, attention is a scarce 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)), and price limits (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. Indeed, as of February 2009, Google accounted for 72.1% of all search queries performed in the United States.[2] The search volume reported by Google is thus likely to be representative of the 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 have 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. Ginsberg et al. (2009) similarly find that search data for 45 terms related to influenza predicted flu outbreaks 1 to 2 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" (p. 1014).

Google makes the Search Volume Index (SVI) of search terms public via the product Google Trends (http://www.google.com/trends). Weekly SVI for a

[1] See, for example, Merton (1987), Sims (2003), Hirshleifer and Teoh (2003), and Peng and Xiong (2006).

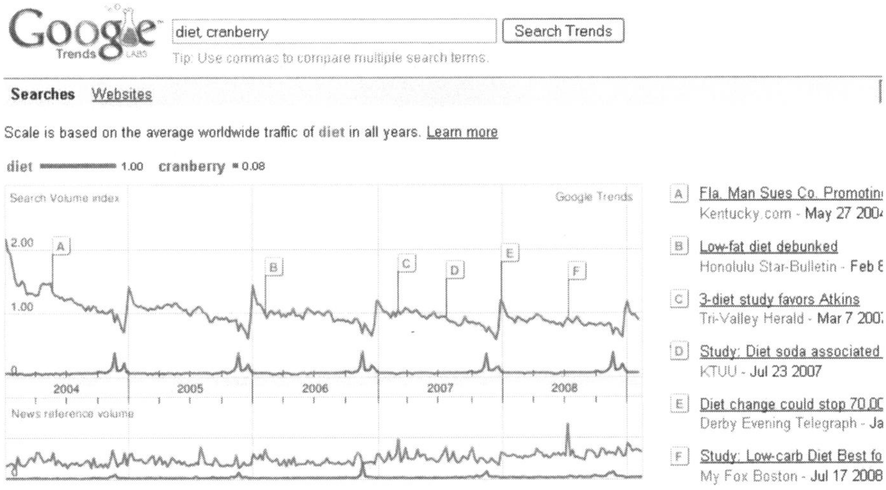
[2] Source: Hitwise (http://www.hitwise.com/press-center/hitwiseHS2004/google-searches-feb-09.php)

search term is the number of searches for that term scaled by its time-series average. Panel A of Figure 1 plots the weekly SVI of the two search terms "diet" and " cranberry" for 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 for "diet" falls during the holiday season and spikes at the beginning of the year, 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, where as the SVI for "cranberry" spikes in November and December, coinciding with the Thanksgiving and Christmas holidays.

To capture 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 the relationship between SVI and existing attention measures. We find that the time-series correlations between (log) SVI and alternative weekly measures of attention such as extreme returns, 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), which is defined as the (log) SVI during the current week minus the (log) median SVI during the previous eight weeks, we find that the majority of the time-series and cross-sectional variation in ASVI remains 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 examine whose attention SVI is 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 find 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 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 their 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 lead, on average, Panel A. Google Trends search for "diet, cranberry"



Panel B. Google Trends search for "MSFT, AAPL"

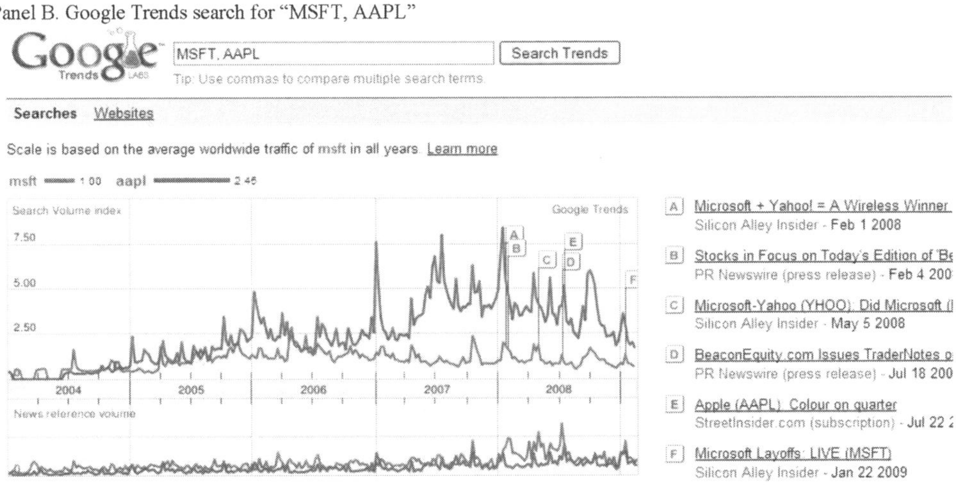


Figure 1. Illustrations of Google Trends search. Panel A represents the graphical output for a Google Trends search of "diet, cranberry." The graph plots weekly aggregate search frequency (SVI) for both "diet" and "cranberry." The SVI for "diet" is the weekly search volume for "diet" scaled by the average 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."

to net buying from these uninformed traders. Within the framework of Barber and Odean (2008), a positive ASVI should predict higher stock prices in the short term and price reversals in the long run. Furthermore, we expect to find stronger attention-induced price pressure among stocks in which individual investor attention matters the most.

Our empirical results based on ASVI as a measure of retail attention strongly support the hypotheses of Barber and Odean (2008). Among our sample of Russell 3000 stocks, stocks that experience an increase in ASVI this week are associated with an outperformance of more than 30 basis points (bps) on a characteristic-adjusted basis 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 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 to predict both a significant initial price increase and a 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 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% 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 experiences large positive ASVI during the week *prior to* the IPO to the group of IPOs that experiences smaller ASVI, we find that the former group outperforms the latter by 6% 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 of media coverage, as discussed in Liu, Sherman, and Zhang (2009). Our results are different, however, from those in Liu, Sherman, and Zhang (2009), who find that increased pre-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.[3]

The rest of the paper is organized as follows. Section I describes data sources and how we construct the aggregate Google SVI variable. Section II compares our SVI measure to alternative proxies of investor attention and examines additional factors that drive our SVI measure. Section III provides direct evidence that SVI captures the attention of retail investors. Section IV tests the price pressure hypothesis of Barber and Odean (2008) in various settings. Section V concludes.

I. 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 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 U.S. companies, representing more than 90% of the total U.S. equity market capitalization. We obtain the membership of the Russell 3000 index directly from Frank Russell and Company. To eliminate survivorship bias and the impact of index addition and deletion, we examine all 3,606 stocks 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 for which 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" for online shopping rather than 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 likely that she is interested in financial information about the stock of Apple Inc.

[3] However, there is no inherent inconsistency in these two seemingly different results. SVI is likely to capture the attention of less sophisticated retail investors, while pre-IPO media coverage is likely to reflect information demand and attention of institutional investors, as suggested in Liu, Sherman, and Zhang (2009).

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.

We are cautious about using tickers with 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 attention paid 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 the "noisy" tickers we identified (about 7% of all Russell 3000 stocks).

Panel B of Figure 1 plots the SVI of Apple's ticker (AAPL) against that of 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 that 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 3,606 stocks in our sample (i.e., all stocks ever included in the Russell 3000 index during our sample period), we employ a web crawling program that inputs each ticker and uses the Google Trends' option to download the SVI data into a CSV file.[4] We do this for all 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 zero value for that ticker's SVI.[5] Of our 834,627 firm-week observations, 468,413 have a valid SVI.

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

[4] 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 are usually above 97%. In addition, we also find that if we restrict our analysis to a subset of SVIs for which the sampling error standard deviation reported by Google Trends is low, we get stronger results.

[5] The truncation issue almost certainly works against us as we analyze price pressure in this paper. As our empirical results suggest, price pressure is typically stronger among small stocks. These are precisely the set of stocks that, on average, will have less search and be removed from the sample due to Google's truncation.

name in CRSP. Where there are differences between the reports, we use Google Insights' "related search" feature to determine which query is most common.[6] 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 that 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 the Dow Jones archive and comprise all Dow Jones News Service articles and *Wall Street Journal* articles about Russell 3000 firms over our sample period. Each article in the data set is indexed by a set of tickers that we date-match to CRSP. A news observation at the weekly (monthly) level in our data set 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 (2010) 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 instead in multiple "chunks"). According to Tetlock (2010, p. 3538), "... stories consisting of more newswire messages are more likely to be timely, important, and thorough." Finally, because the Dow Jones archive does not systematically index (by ticker) a company's news media coverage prior to its IPO, we manually searched Factiva to obtain the media coverage attributes for the IPO sample.

We collect all 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 (LPs), and stocks for which the final offering price is below five dollars. We also require the stock's common shares to be traded on the NYSE, Amex, or NASDAQ exchange with a valid closing price within 5 days of the IPO date.

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

[6] For each term entered into Google Insights (http://www.google.com/insights/), it returns 10 "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 have 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."

centers in the United States, and provides various transaction cost and execution quality statistics based on the Dash-5 reports. The main variables of interest from the MSI database include the number of shares executed and the number of orders 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 Standard and Poor's COMPUSTAT, and analyst information is obtained from I/B/E/S. Table I defines all variables used in this paper.

II. What Drives SVI?

In this section, we examine what drives SVI and compare SVI to other common proxies for attention. We first present simple contemporaneous correlations among (log) SVI and other variables of interest (see Table I for definitions), measurable at a weekly frequency in Table II. These correlations are first computed in the time series for each stock with a minimum of 1 year of data and then averaged across stocks.

In general, the correlations between SVI and the 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 locations, or searching for job opportunities, 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 further 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 5.9%, and the correlation between *Abnormal Turnover* and *Log(SVI)* is 3.5%. Such low correlation may be attributed to the fact that both returns and turnover are equilibrium outcomes that are functions of many 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 3.5% (*Chunky News*) to 5.0% (*News*). There are several reasons for such low correlations. First, overall newspaper coverage is surprisingly low. Fang and Peress (2009) report that over 25% of NYSE stocks are not featured in the press in a typical year. The number is even higher for NASDAQ stocks (50%). While SVI measures investor attention continuously over the year, news coverage of a typical firm is sporadic. 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 were

Table I
Variable Definitions

Variable	Definition
Variables from Google Trends	
SVI	Aggregate search frequency from Google Trends based on stock ticker
ASVI	The log of SVI during the week minus the log of median SVI during the previous 8 weeks
Name_SVI	Aggregate search frequency based on company name
APSVI	The log of PSVI (aggregate search frequency based on the main product of the company) during the week minus the log of median PSVI during the previous 8 weeks
Variables from Dash-5 reports	
Percent Dash-5 Volume	Ratio between Dash-5 trading volume and total trading volume during the previous month
Madoff	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)
Other variables related to investment attention / sentiment	
Ret	Stock return
Abn Ret	Characteristic-adjusted return as in Daniel et al. (1997)
Turnover	Trading volume
Abn Turnover	Standardized abnormal turnover as in Chordia, Huh, and Subrahmanyam (2007)
Market Cap	Market capitalization
# of Analysts	Number of analysts in I/B/E/S
Advertising Expense/Sales	Ratio between advertisement expense and sales in the previous fiscal year, where we set advertisement expenditure to zero if it is missing in COMPUSTAT
News	Number of news stories in the Dow Jones news archive
News Dummy	Dummy variable that takes the value of one if News variable is positive
Chunky News	Number of news stories with multiple story codes in the Dow Jones news archive
Chunky News Dummy	Dummy variable that takes the value of one if Chunky News variable is positive
Chunky News Last Year	Number of Chunky News stories in the last 52 weeks
Frac_Neg_H4	Media-based stock-level sentiment measure. Following Tetlock (2007), 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 over the entire collection of news articles about the stock (excluding so-called "stop words") within that week, as well as the 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. Negative sentiment words are defined using the Harvard IV-4 dictionary.

(*continued*)

Table I—*Continued*

Variable	Definition
Frac_Neg_LM	Similar to Frac_Neg_H4 except that negative sentiment words are defined in Loughran and McDonald (2010)
Variables related to IPO	
First-day return	First CRSP available closing price divided by the offering price minus one
Media	Log of the number of news articles recorded by Factiva (using the company name as the search criterion) between the filing date (inclusive) and the IPO date (exclusive), normalized by the number of days between the filing date and the IPO date
Price Revision	Ratio of the offering price divided by the median of the filing price
DSENT	Baker-Wurgler (2006) monthly investor sentiment change (orthogonal to macro variables) the month the firm goes public, obtained from Jeffrey Wurgler's website (http://pages.stern.nyu.edu/~jwurgler)
Offering Size	Offering price multiplied by the number of shares offered
Age	Number of years between the firm's founding year and the IPO year, obtained from Jay Ritter's website and supplemented by hand-collected information from various sources
Asset Size	Firm's total assets prior to IPO
CM Underwriter Ranking	Carter-Manaster (1990) ranking of lead underwriter, obtained from Jay Ritter's website
VC Backing	Dummy variable taking a value of one if the IPO is backed by a venture capital firm, and zero otherwise
Secondary Share Overhang	Secondary shares offered/(IPO shares offered + secondary shares offered).
Past Industry Return	Fama-French 48-industry portfolio return corresponding to the industry classification of the IPO at the time of the public offering

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, p. 129), is broadly defined as "a belief about future cash flows and investment risks that is not justified by the facts at hand." A priori, it is not clear how investor attention and sentiment should be related to each other. On the one hand, because 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. On the other hand, increased attention paid to genuine news may increase the rate at which information is incorporated into 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 1.4% to 2.3%.

Table II
Correlations

The table shows the correlations among variables of interest measured at weekly frequency. The variables are defined in Table I. The sample period is from January 2004 to June 2008.

	log(SVI)	log(Name_SVI)	Absolute Abn Ret	Abn Turnover	log(1 + News)	log(1 + ChunkyNews)	Frac_Neg_H4
log(Name_SVI)	0.093						
Absolute Abn Ret	0.059	0.093					
Abn Turnover	0.035	0.097	0.311				
log(1 + News)	0.050	0.155	0.199	0.181			
log(1 + ChunkyNews)	0.034	0.151	0.237	0.227	0.637		
Frac_Neg_H4	0.023	0.058	0.109	0.107	0.383	0.257	
Frac_Neg_LM	0.014	0.035	0.077	0.081	0.175	0.133	0.664

Table III

Vector Autoregression (VAR) Model of Attention Measures

We compare four weekly measures of attention using vector autoregressions (VARs). The variables are defined in Table I. We run the VAR for each stock with at least 2 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, respectively.

	Lagged 1 Week				
	log(SVI)	log(turnover)	Absolute Abn Ret	log(1 + Chunky News)	R^2
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 Abn Ret	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

We next 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 (see Table I for definitions) include *Log*(*SVI*), *Log*(*Turnover*), *Absolute Abn Ret*, and *Log*(*1+Chunky News*). 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 2 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 III 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 by Bessembinder, Maxwell, and Venkataraman (2006). A simple reverse Fama and MacBeth (1973) method that does not account for cross-autocorrelations in error terms produces even smaller p-values.[7]

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 use current-week *Log(Turnover), Absolute Abn Ret,* and *Log(1+Chunky News)* as the dependent variables. These positive coefficients suggest that SVI captures investor attention in a more timely fashion than extreme returns or news. This is not surprising: to the extent that investors trade only after paying attention to a stock and their trading causes price pressure that persists 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 prescheduled 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 Abn Ret* 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 for attention in a set of regressions. Our key variable of interest in the paper, ASVI, is defined as

$$ASVI_t = \log(SVI_t) - \log\left[Med(SVI_{t-1}, \ldots, SVI_{t-8})\right], \tag{1}$$

where $\log(SVI_t)$ is the logarithm of SVI during week t, and $\log[Med(SVI_{t-1}, \ldots, SVI_{t-8})]$. is the logarithm of the median value of SVI during the prior 8 weeks.[8] 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 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 IV, where the dependent variable is always ASVI. All regressions reported in this table contain week fixed effects, and the robust 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 *Chunky News Dummy* is more important in driving ASVI than *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^2 of these

[7] The reverse Fama-MacBeth (1973) regression carries out time-series regressions first, then takes the cross-sectional average of coefficients from the first-stage regressions.

[8] Our main results are robust to the length of the rolling window (4 weeks, 6 weeks, 10 weeks, etc.).

Table IV

Abnormal SVI (ASVI) and Alternative Measures of Attention

The dependent variable in each regression is abnormal ASVI. ASVI and independent variables are defined in Table I. Robust standard errors clustered by firm are in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. 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 Abn Ret	0.131***	0.127***	0.127***	0.127***	0.129***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Abn 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+ # 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	411,930	411,930	411,930	411,930	411,930
Week fixed effects	YES	YES	YES	YES	YES
Clusters (firms)	2,435	2,435	2,435	2,435	2,435
R^2	0.03304	0.03315	0.03315	0.03315	0.03318

regressions is only about 3.3%, 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. However, noise is likely to bias against us finding any reliable results.

III. SVI and Individual Investors

Whose attention does SVI capture? Intuitively, people who search financial information related to a stock in Google are more likely to be individual or retail investors since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg terminals.[9] In this section,

[9] For example, we find that there is a significant jump in weekly SVI of about 10% (t-statistic > 9) for stocks picked by Jim Cramer on CNBC's *Mad Money*. Engelberg, Sasseville, and Williams (2010) argue that the show primarily captures individual investors' attention.

we provide direct evidence that changes in investor attention measured by SVI are indeed related to trading by individual investors.

Traditionally, trade size from the ISSM and TAQ databases is used to identify retail investor transactions.[10] However, after decimalization in 2001, order splitting strategies became prominent (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 size.

Instead, we obtain retail orders and trades directly from Dash-5 monthly reports. Since 2001, by Rule 11Ac1-5 and Regulation 605, the U.S. Security and Exchange Commission (SEC) requires every market center to make public monthly reports 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.[11] 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.

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 to 499 shares, (2) 500 to 1,999 shares, (3) 2,000 to 4,999 shares, and (4) 5,000 to 9,999 shares.

The Dash-5 reports allow us to compute monthly changes in orders and turnover from individual investors. We then relate these changes to monthly changes in SVI in Table V. Monthly SVI is computed by aggregating weekly SVIs assuming daily SVI is constant within the week. We consider several alternative proxies of attention as control variables and they are defined in Table I.

We also control for other stock characteristics that might be related to turnover. They include: the book-to-market value of equity, where the book

[10] See, for example, Easley and O'Hara (1987) for a theoretical justification and Lee and Radhakrishna (2000), Hvidkjaer (2008), and Barber, Odean, and Zhu (2009), among others, for empirical evidence.

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

Table V
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 to 1,999 shares and (2) 100 to 9,999 shares. Panel B considers orders in the 100 to 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 Bernard L. Madoff Investment Securities LLC. NYSE/ARCH (columns 3 and 4) refer to the 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 (ΔOrder) or monthly changes (log difference) in the individual turnover (ΔTurnover) on several variables. These include monthly SVI change (ΔSVI), alternative measures of attention and other stock characteristics. ΔSVI is the difference between the logarithm of SVI during month t and the logarithm of SVI during month $t-1$, aggregated from weekly SVI. Other independent variables are defined in Table I. All regressions contain monthly fixed effects. Robust standard errors, reported in parentheses, are clustered at the stock level. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. The sample period is from January 2004 to June 2008.

Panel A. Regressions of monthly Dash-5 reported order and turnover changes by order sizes

	Order Size: 100–1,999 shares		Order Size: 100–9,999 shares	
	ΔOrder (1)	ΔTurnover (2)	ΔOrder (3)	ΔTurnover (4)
ΔSVI ($t-1$, 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)
Absolute 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)
Advertising Expense/Sales ($t-1$)	−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^2	0.250	0.288	0.262	0.300

(continued)

Table V—*Continued*

Panel B. Regressions of monthly Dash-5 reported order and turnover changes by market center

	Madoff		NYSE/ARCH		Comparison	
	ΔOrder (1)	ΔTurnover (2)	ΔOrder (3)	ΔTurnover (4)	ΔOrder (5)	ΔTurnover (6)
Δ SVI (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)
ΔSVI × 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)
Absolute 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)
Advertising Expense/Sales (t−1)	−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^2	0.131	0.127	0.299	0.291	0.173	0.191

value of 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 $(t-1)$; the percentage of stocks held by all S34-filing institutional shareholders at the end of quarter $(Q-1)$; the standard deviation of the individual stock return estimated from daily returns during quarter $(Q-1)$; the difference between the natural logarithm of total stock turnover reported by CRSP in month $(t-2)$ and month $(t-1)$; the 1-month return prior to current month t; the cumulative stock return between months $(t-13)$ and $(t-2)$; and the cumulative stock return between months $(t-36)$ and $(t-14)$.

In Panel A of Table V, we examine changes in individual trading across all markets centers. We first consider the smaller order size categories (100 to 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 1% increase in SVI leads to a 0.0925% increase in individual orders (regression 1). This positive correlation is statistically significant at the 1% level after controlling for alternative proxies for attention and other trading-related stock characteristics. It is not too surprising that several alternative proxies for attention are also significant because they might be mechanically related to trading. For example, trading can correlate with absolute returns or market capitalization 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 to 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 V, and we therefore use all order size categories hereafter.

Although retail traders are thought to be uninformed on average, we do not rule out the possibility that *some* individual traders may be informed. 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 informed individual investors are often routed to and executed at market centers that pay for order flow. One well-known market center is now-defunct Bernard L. Madoff Investment Securities LLC (Madoff). In contrast, orders from more informed investors often go to the NYSE for NYSE stocks and Archipelago for NASDAQ stocks. These venues do not pay for order flow and 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 uninformed 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 V. 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 for attention and other trading-related stock characteristics, a 1% increase in SVI translates to a 0.264% increase in individual orders and a 0.297% 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% and 0.131%). In contrast, the same 1% increase in SVI only translates to a 0.092% increase in individual orders and a 0.104% 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 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% increase in SVI leads to a 0.109% greater increase in individual orders and a 0.0951% 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 may not be capturing the attention of less informed retail investors.

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

IV. 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 of 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 that attention shocks lead to net buying by retail traders. Because retail traders are uninformed on average, this should lead to temporarily higher returns. To the extent that ASVI is a direct measure of retail attention, we can directly test the price pressure hypothesis of Barber and Odean (2008). Specifically, we expect large ASVI to result in increased buying pressure that pushes stock prices up temporarily. We first investigate such price pressure in the context of a cross-section of Russell 3000 stocks and then in the context of IPOs. Given the lack of trading data prior to 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.

A. Russell 3000 Stock Sample

We first investigate the empirical relation between ASVI and future stock returns for Russell 3000 stocks in our sample. We use a Fama-MacBeth (1973) cross-sectional regression to account for time-specific economy-wide shocks. Each week, we regress future DGTW abnormal returns (measured in basis points, or bps) at different horizons on ASVI and other control variables. The regression coefficients are then averaged over time and standard errors are computed using the Newey-West (1987) 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 effect of a one-standard-deviation change in that variable). These regression results are reported in Table VI.

In column 1, the dependent variable is next week's DGTW abnormal return. We find strong evidence of positive price pressure following an increase in individual attention as measured by ASVI. A one-standard-deviation increase in ASVI leads to a significant positive price change of 18.7 bps among Russell 3000 stocks. Moreover, this result holds primarily in two important cross-sections of the data. First, if a price increase reflects price pressure due to individual buying activity, we would expect it to be stronger among small stocks, which are typically associated with a larger price impact. This is exactly what we find in the data. 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. In fact, we confirm through both a portfolio sorting exercise and regression analysis that the positive price pressure is only present among the smaller half of our Russell 3000 stock sample.[12]

Second, we would expect price pressure to be stronger among stocks that are traded more by individual investors. We measure retail trading directly using *Percent Dash-5 Volume*, defined as the ratio between Dash-5 trading volume and total trading volume during the previous month. We find the interaction between this retail trading measure and ASVI is significant in predicting first-week abnormal returns, which suggests a stronger price increase among stocks traded mainly by retail investors, again supporting the price pressure hypothesis of Barber and Odean (2008).

Note that the positive, significant coefficient on ASVI in column 1 is 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 *Chunky News Dummy*, which measures whether there is a 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

[12] These additional results are reported in the Internet Appendix, available online in the "Supplements and Datasets" section at http://www.afajof.org/supplements.asp.

Table VI

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 4 weeks and during weeks 5 to 52. Independent variables are defined in Table I. 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 (1987) formula with eight lags. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. 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 Abn Ret	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)
Abn Turnover	2.398**	2.309**	2.022	0.316	10.531
	(1.204)	(1.144)	(1.404)	(1.098)	(10.109)
Observations per week	1,499	1,498	1,497	1,496	1,414
R^2	0.0142	0.0119	0.0112	0.0111	0.0170

variable with a continuous news variable, the regression coefficient ceases to be significant.

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

While the positive coefficient on ASVI in column 1 is consistent with the price pressure hypothesis, it could also simply reflect positive fundamental information about the firm that is captured by ASVI on a more timely basis. For example, suppose a company announces an innovation in 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 gradually gets incorporated into the stock price.

We have two pieces of evidence that is inconsistent with such 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 a valid APSVI, we set APSVI to zero.

If the information story is true, we would expect an even larger 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 actually negative although its magnitude is small (a -2.5 bp price drop for a one-standard-deviation increase in APSVI).

The second distinguishing feature between the price pressure hypothesis and the information-based alternative is the prediction 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 reflects fundamental information about the firm, then no long-run reversal would be expected.

We examine long-run returns in regression 5. Following Barber and Odean (2008), we skip the first month and look at the returns from weeks 5 to 52. We find a negative coefficient of -28.9 bps on ASVI, similar to the magnitude of total initial price pressure in the first 2 weeks, suggesting that the initial price pressure is almost entirely reversed in 1 year. However, the negative coefficient is marginally insignificant (t -value = 1.69). This is not too surprising: given our short 5 1/2-year sample, we do not have many independent 48-week return observations so the regression coefficient is less likely to be significant after the Newey-West (1987) autocorrelation correction. However, the regression results reported in the Internet Appendix suggest that such reversals *are* significant among the smaller half of the Russell 3000 stocks. Overall, it is important to note that ASVI seems to be the only measure of attention that predicts both the initial price increase and subsequent long-run price reversal. The existence of long-run reversal is more consistent with the price pressure hypothesis than the information hypothesis.

Table VII reports the results of several robustness checks. Panels 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.[13] The regression results are qualitatively similar in the two subsample periods although slightly

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

Table VII

ASVI and Russell 3000 Stock Returns: Robustness

We repeat the analysis in Table VI for 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.

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5–52 (5)
Panel A. January 2004 to June 2006					
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 Abn Ret	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)
Chunky News Dummy	3.252	2.141	−2.248	−2.128	57.719
	(2.792)	(2.943)	(2.977)	(2.333)	(47.286)
Abn Turnover	1.490	1.112	2.755	0.101	−0.340
	(1.615)	(1.321)	(1.764)	(1.394)	(15.244)
Observations per week	1,381	1,381	1,380	1,379	1,314
R^2	0.0128	0.0112	0.0106	0.0102	0.0146
Panel B. July 2006 to June 2008					
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)

(continued)

Table VII—*Continued*

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5–52 (5)
Absolute Abn Ret	−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)
Chunky News Dummy	4.054	0.432	−5.781	2.509	1.142
	(2.994)	−3.904	−4.038	(2.988)	(22.158)
Abn Turnover	3.524**	3.794**	1.112	0.584	24.016**
	(1.771)	−1.836	−2.25	(1.783)	(11.769)
Observations per week	1,645	1,644	1,643	1,641	1,538
R^2	0.0160	0.0128	0.0118	0.0122	0.0199
Panel C. Excluding noisy tickers					
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 Abn Ret	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)
Chunky News Dummy	3.121	0.452	−4.264	−0.872	13.914
	(2.118)	(2.669)	(2.597)	(2.157)	(27.867)
Abn Turnover	2.088	2.781**	3.089**	0.344	23.410**
	(1.355)	(1.237)	(1.436)	(1.293)	(10.459)
Observations per week	1,187	1,187	1,186	1,185	1,122
R^2	0.0152	0.0123	0.0119	0.0113	0.0167

stronger in the second. Panel C of Table VII reports the regression results after we exclude the "noisy" tickers such as "GPS," " DNA," "BABY," "A," " B," and "ALL." Panel C shows that removing these "noisy" tickers hardly changes our regression results.

To summarize, we find increases in ASVI predict increases in returns in the following 2 weeks, especially among small stocks and those traded by retail investors. Moreover, this initial price pressure is almost completely reversed in 1 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 support for the price pressure hypothesis of Barber and Odean (2008).

B. Initial Public Offerings IPO Sample

A natural venue to examine the effect of retail attention on asset prices is a stock's 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 around the issuance. For the set of IPO stocks that receive more retail attention prior to 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 retail investors can contribute to higher first-day returns. Subsequently, for the set of IPO stocks bid up by retail investors, when the price pressure 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 the 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 data set 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 returns, and negatively correlated with IPO performance up to 1 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 more likely to be sentiment traders suffering from various behavioral biases.

We again measure retail attention prior to the IPO using ASVI. Because there is no ticker widely available or known to the public prior to the IPO, we use the company name provided by the SDC to search for the stock in Google Trends to obtain the SVI. For the sample of IPOs from 2004 to 2007, we are able to identify 185 IPOs with sufficient searches that their SVIs are not missing.[14]

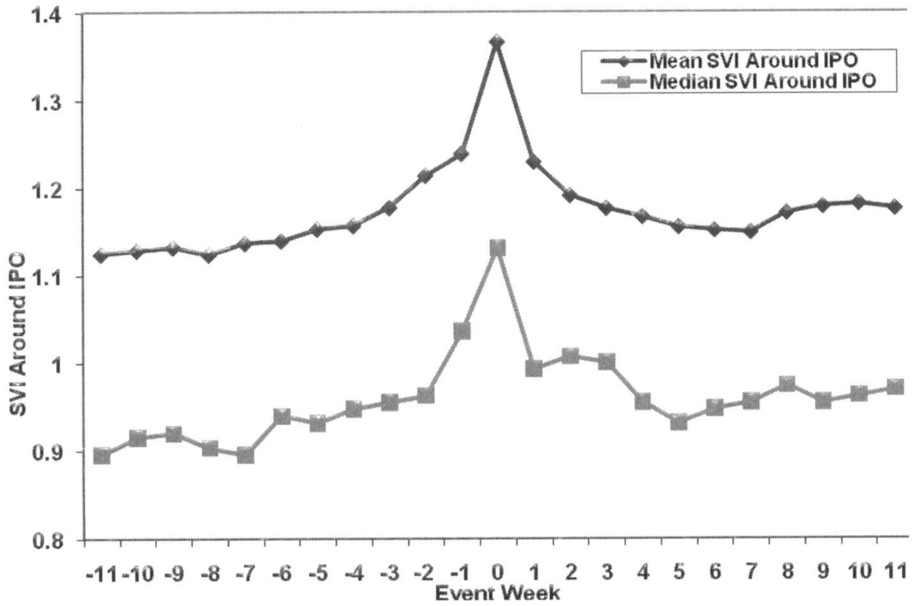
We first confirm that there are significant changes in SVI around the time of the IPO. Panel A of Figure 2 illustrates the cross-sectional mean and median of the SVI (in logarithm) around the IPO week (week 0). We observe a significant upward trend in SVI starting 2 to 3 weeks prior to the IPO week, followed by 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 ASVI around the IPO week. The SVI on an IPO stock jumps by 20% (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 investors' attention is not permanent. The SVI reverts to its pre-IPO level 2 to 3 weeks after the IPO.

Next, 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 has first-day average returns of 10.90% while the set of IPOs with high ASVI has much higher first-day average returns of 16.98%. The difference between the two average first-day returns is about 6.08%. Both t-tests and nonparametric Wilcoxon tests indicate that the difference is statistically significant at the 1% level.

We formalize the analysis using regressions in Table VIII. 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 by 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 Factiva (using company name as the search criterion) between 1 day after the filing date and 1 day before the IPO date, normalized by the number of days between the filing date and the IPO date. 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 interpretation 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 median 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

[14] From the SDC new issues 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 for some IPO stocks. First, individuals may not use the SDC company name to search for the stock in Google. Second, Google Trends truncates the output and returns missing values for SVIs with insufficient searches. Unfortunately, we have not been able to obtain the exact criteria used by Google to determine the truncation threshold.

Panel A. Cross-sectional average SVI around IPO



Panel B. Cross-sectional average ASVI around IPO

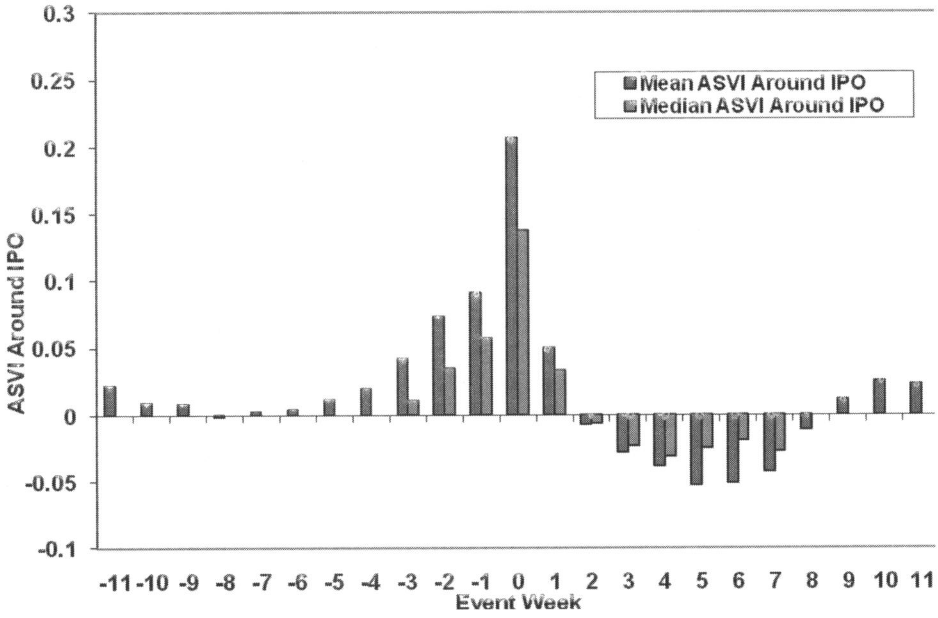
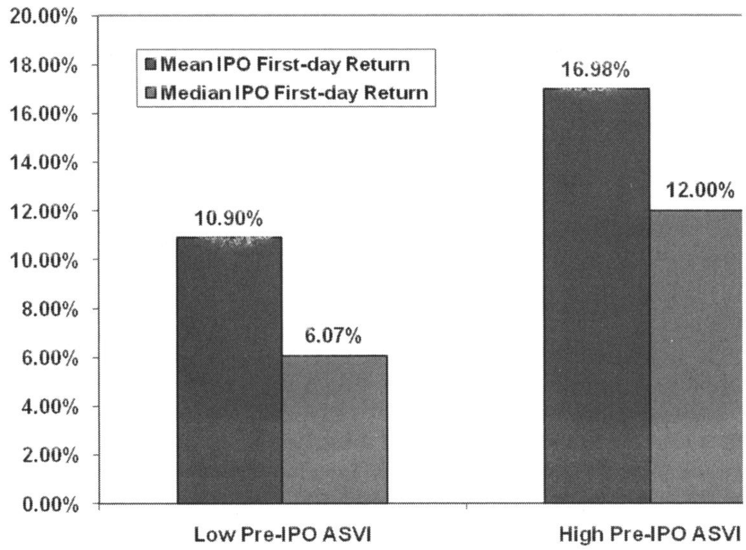


Figure 2. Average SVI and Abnormal SVI (ASVI) around IPO. Panel A plots the cross-sectional mean and median of the search volume index (SVI; in logarithm) around the week of the IPO. Panel B plots the cross-sectional mean and median of the ASVI around the week of the IPO. Week 0 is the week of the IPO. The sample period is from January 2004 to December 2007. There are 185 IPOs with valid SVI in this sample.

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



Panel B. Pre-IPO ASVI and cross-sectional average industry-adjusted IPO cumulative returns (4 to 12 months)

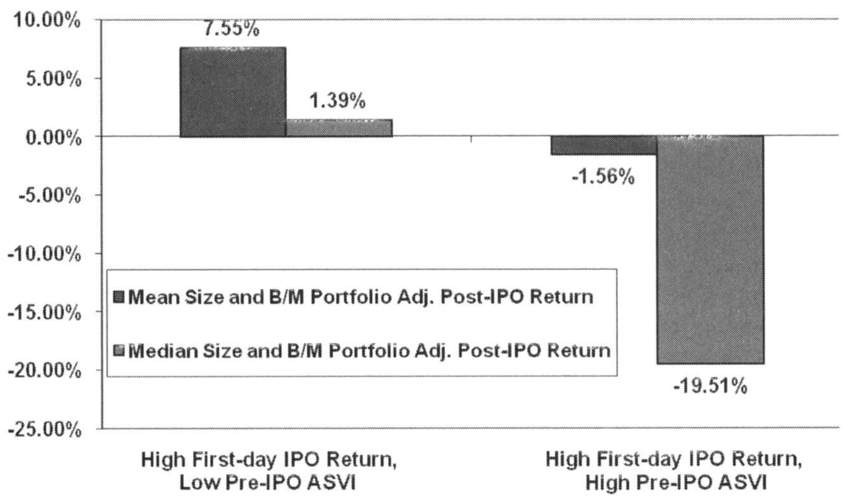


Figure 3. Pre-IPO ASVI, average first-day IPO returns and long-run IPO returns. Panel A plots pre-IPO ASVI and average first-day returns. Panel B plots pre-IPO ASVI and the size and book-to-market matched portfolio adjusted cumulative abnormal returns from week 5 to week 52. The sample period is from January 2004 to December 2007. There are 185 IPOs with a valid SVI in the sample.

(see Ibbotson and Jaffe (1975), Ritter (1984), and 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 activity, we still control for the impact of time-varying aggregate market sentiment using a third additional variable, *DSENT*. Developed by Baker and Wurgler (2006) and obtained from Jeffrey Wurgler's website, *DSENT* is the monthly investor sentiment change (orthogonal to macro variables) at the month the firm goes public. 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 VIII. These characteristics are defined in Table I.

Regression 1 in Table VIII confirms that ASVI, on a stand alone basis, strongly predicts first-day IPO return. The regression coefficient of 0.275 suggests that a one-standard-deviation increase in ASVI (0.168) leads to a 4.62% (=0.168 × 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^2 in our sample of IPOs. Regression 3 shows that *Price Revision* is by far the strongest predictor of the first-day return. The 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 do 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 through 8 in Table VIII control for other IPO characteristics. The predictive power of all four variables remains. 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 that ASVI drives out *Media*, although this comes from an increase in *Media*'s standard error rather than a decrease in its point estimate in the full specification. Nevertheless, when all variables are included in the full specification (column 9), the *only* stock-specific attention measure that predicts first-day returns is ASVI. Moreover, 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, a one-standard-deviation increase in ASVI still leads to a 3.18% (=0.168 × 0.189) higher first-day return.

In a third analysis, 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 market capitalization and book-to-market equity matched portfolio-adjusted cumulative IPO returns from weeks 5 to 52 after the IPO. The choice of this return horizon is consistent with Figure 2, which shows that the level of retail investor attention largely reverts to the pre-IPO level by the end of week 4.[15] We focus on the IPOs that experience large first-day returns and further divide

[15] We also experiment with skipping the first 3 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.

Table VIII

Pre-IPO Abnormal Search Volume (ASVI) and IPO First-Day Return

This table regresses IPO first-day returns on pre-IPO week abnormal search volume (ASVI) and IPO characteristics. The dependent variable is the individual IPO's first-day return. Independent variables are defined in Table I. 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 a valid SVI (searched using company names) are retained in the sample. Only IPOs with the first available CRSP closing price less than or equal to 5 days from the IPO date are retained. Standard errors (in parentheses) are clustered by the offering year and quarter. *, **, and *** represent significance 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^2	0.052	0.037	0.235	−0.001	0.217	0.214	0.288	0.194	0.340

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 do 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%. Both t-tests and nonparametric Wilcoxon tests indicate that the difference is statistically significant at the 1% level.

We formalize the analysis using cross-sectional regressions in Table IX, where we include the same control variables as in Table VIII. Panel A reports the results when the dependent variable is the cumulative IPO raw return from weeks 5 to 52 after the 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 predict long-run underperformance (as seen in regression 2). This result is consistent with our conjecture that for IPOs with high first-day returns that also experience increases in retail investor attention, the high first-day returns are partly driven by price pressure and hence will revert in the long run. In addition, the interaction terms 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 *Price Revision* and *Media* capture other aspects of the IPO price-setting process. The insignificance of the offering price revision variable suggests that it is individual investor attention (and not that of institutions) that contributes to the high first-day IPO return that is eventually reversed in the long run.

We also repeat the regression analysis using adjusted long-run stock returns post-IPO. Panel B of Table IX 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 5 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 experience 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 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).

C. An Alternative Interpretation

Now we discuss an alternative interpretation of ASVI's predictability for IPO returns. It could be the case that market participants have an *expectation*

Table IX

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 5 years) returns (Panel C) during the 4 to 12 months after the IPO. The dependent variable in Panel A is the individual IPO's cumulative return during the $[w+5, w+52]$ week window after the IPO, where week w is the week the company went public. The dependent variable in Panel B is the individual IPO's cumulative return during the $[w+5, w+52]$ week window after the IPO 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 IPO adjusted by the corresponding size and book-to-market equity matched portfolio (excluding recent IPO stocks in the past 5 years) returns during the same event window. To generate the size and book-to-market equity matched portfolio returns of non-IPOs, we match the first available market capitalization of the IPO with the immediate past June's NYSE market capitalization quintile break point, and then match the 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. The book value of the IPO is the first available book value of equity immediately after the IPO, and the market equity is the first available market capitalization of the IPO. The independent variables are defined in Table I. 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 a valid SVI (searched using company names) are retained in the sample. Only IPOs with the first available CRSP closing price less than or equal to 5 days from the IPO date are retained. Standard errors (in parentheses) are clustered by the offering year and quarter. *, **, and *** represent significance 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 × 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 × 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 × 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 × 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)

(*continued*)

Table IX—*Continued*

Panel A. Pre-IPO abnormal search volume (ASVI) and IPO returns

	Dependent Variable: IPO Return					
	(1)	(2)	(3)	(4)	(5)	(6)
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^2	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 × 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 × 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 × 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 × 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)

(*continued*)

Table IX—*Continued*

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)
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^2	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 returns

	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 × 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 × First-Day Return			0.0001			−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 × 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 × 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

(*continued*)

Table IX—*Continued*

Panel C. Pre-IPO abnormal search volume (ASVI) and book-to-market equity/size matched portfolio adjusted IPO returns

	Dependent Variable: Size and B/M Matched Portfolio Adjusted IPO Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
	(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^2	0.011	0.005	0.017	0.016	0.015	0.020

of IPO first-day returns and that they search a lot (a little) prior to the IPO when they expect first-day return to be high (low). Therefore, higher expected first-day returns *cause* higher ASVI (i.e., the "anticipation hypothesis"), not the other way around (i.e., the "attention hypothesis").[16]

There are two pieces of evidence that suggest the anticipation hypothesis cannot fully explain our results. First, we directly measure market expectations of first-day returns using IPO SCOOP. IPO SCOOP is an independent research firm (not affiliated with underwriters) that surveys Wall Street investment professionals and provides a rating-based forecast of a forthcoming IPO's first-day performance.[17] Then, we rerun the regressions similar to Table VIII by including IPO SCOOP's rating-based forecast of first-day return. The results are reported in the Internet Appendix. We find that while market expectations clearly predict first-day returns, ASVI's predictability for first-day returns remains economically and statistically significant. In fact, the point estimate and statistical significance of ASVI hardly change. In addition, we find that neither the IPO SCOOP ratings nor its interaction with first-day returns have any predictability for post-IPO returns.

Second, while it's possible that expectations about first-day returns explain the correlation between ASVI and first-day returns, it does not explain ASVI's

[16] We thank an anonymous referee for suggesting and encouraging us to explore this possibility.
[17] It turns out that the IPO SCOOP rating is a powerful predictor of first-day returns. For example, our sample of IPOs with below-median ratings have first-day returns of 7.07%, while IPOs with above-median ratings have first-day returns of 26.08%.

predictability for IPO return reversal. It seems less reasonable to believe that investors, anticipating a return reversal of an IPO, search more for it before the IPO. In contrast, the attention hypothesis explains ASVI's predictability for both first-day returns and long-run reversals. In our view, while we certainly cannot rule out the anticipation hypothesis, the attention hypothesis is a more consistent explanation of the evidence.

V. Conclusion

Existing measures of investor attention such as turnover, extreme returns, news, and advertising expense are indirect proxies. In this paper, 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 first show that SVI is correlated with but different from existing proxies for 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 of Barber and Odean (2008). We find that an increase in SVI for Russell 3000 stocks predicts higher stock prices in the next 2 weeks and an eventual price reversal within the year. SVI also contributes to the large first-day return and long-run underperformance for a sample of IPO stocks.

Beyond testing theories of attention, this paper also illustrates the usefulness of search data in financial applications. To our knowledge, this paper and Mondria, Wu, and Zhang (2010) are the first to use internet search volume in financial economics. As empiricists, we rarely observe the aggregate interest of investors other than via equilibrium outcomes such as volume and returns. Search volume is an objective way to reveal and quantify the interests of investors and therefore should have many other potential applications in finance. We leave such applications 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, 785–818.

Barber, Brad M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 21, 151–186.

Battalio, Robert, 1997, Third market broker-dealers: Cost competitors or cream skimmers? *Journal of Finance* 52, 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, 15–58.

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

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

Chiang, Yao-Min, Yiming Qian, and Ann E. Sherman, 2010, Endogenous entry and partial adjustment in IPO auctions: Are institutional investors better informed? *Review of Financial Studies*, 23, 1200–1230.

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.

Chordia, Tarun, Sahn-Wook Huh, and Avanidhar Subrahmanyam, 2007, The cross-section of expected trading activity, *Review of Financial Studies* 20, 709–740.

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

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, 2339–2373.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2010, In search of fundamentals, 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, 1039–1074.

Engelberg, Joseph, Caroline Sasseville, and Jared Williams, 2011, Market madness? The case of mad money, *Management Science*, forthcoming.

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* 64, 2023–2052.

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

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.

Grullon, Gustavo, George Kanatas, and James P. Weston, 2004, Advertising, breath of ownership, and liquidity, *Review of Financial Studies* 17, 439–461.

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, New York, NY).

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337–386.

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.

Hvidkjaer, Soeren., 2008, Small trades and the cross-section of stock returns, *Review of Financial Studies* 21, 1123–1151.

Ibbotson, Rorger, and Jeffrey F. Jaffe, 1975, "Hot issue" markets, *Journal of Finance* 30, 1027–1042.

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, 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, London School of Economics and Political Science.

Loughran, Tim, and Bill McDonald, 2011, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance* 66, 35–65.

Loughran, Tim, and Jay Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 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, 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, 483–510.

Mondria, Jordi, Thomas Wu, and Yi Zhang, 2010, The determinants of international investment and attention allocation: using internet search query data, *Journal of International Economics* 82, 85–95.

Newey, Whitney, and Kenneth West, 1987, A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

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

Ritter, Jay, and Ivo Welch, 2002, A review of IPO activity, pricing, and allocations, *Journal of Finance* 57, 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., 2010, Does public financial news resolve asymmetric information? *Review of Financial Studies* 23, 3520–3557.

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