In Search of Attention*

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Abstract

Turnover, extreme returns, news and advertising expense are indirect proxies of investor attention. In contrast, we propose a *direct measure* of investor demand for attention – active attention – using search frequency in Google (SVI). In a sample of Russell 3000 stocks from 2004 to 2008, we find SVI to be correlated with but different from existing proxies of investor attention. In addition, SVI captures investor attention on a more timely basis. SVI allows us to shed new light on how retail investor attention affects the returns to IPO stocks and price momentum strategies. Using retail order execution in SEC Rule 11Ac1-5 reports, we establish a strong and direct link between SVI changes and trading by less sophisticated individual investors. Increased retail attention as measured by SVI during the IPO contributes to the large first-day return and long-run underperformance of IPO stocks. We also document stronger price momentum among stocks with higher levels of SVI, consistent with the explanation of momentum proposed by Daniel, Hirshleifer and Subrahmanyam (1998).

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

— Herbert Simon, Nobel Laureate in Economics

1 Introduction

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

When testing theories of attention, empiricists face a substantial problem: 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 (Gervais, Kaniel, and Mingelgrin, 2001, Barber and Odean, 2008, and Hou, Peng, and Xiong, 2008), news and headlines (Barber and Odean, 2008 and Yuan, 2008), and advertising expense (Grullon, Kanatas, and Weston , 2004, Lou, 2008, and Chemmanur and Yan, 2009). These proxies make the critical assumption that if a stock's return or turnover was extreme or its name was covered 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. In particular, search frequency allows us to shed new light on how retail investor attention affects the returns to initial public offering (IPO) stocks and price momentum strategies. We use aggregate search frequency in Google as a measure of attention for several reasons. First, internet users commonly use a search engine to collect information, and Google continues to be the favorite. In

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

February of 2009, Google accounted for 72.1 percent of all search queries performed in the United States.[2] 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. Google's Chief Economist Hal Varian recently suggested that search data has the potential to predict a variety of economic activities. Choi and Varian (2009) support this claim by providing evidence that search data can predict home sales, automotive sales and tourism. In a recent study, Ginsberg et al. (2008) found that search data for forty-five terms related to influenza predicted flu outbreaks one to two weeks before Centers for Disease Control and Prevention (CDC) reports. The authors conclude that, "harnessing the collective intelligence of millions of users, Google web search logs can provide one of the most timely, broad-reaching influenza monitoring systems available today."

Google makes public the Search Volume Index (SVI) of search terms via its product Google Trends (http://www.google.com/trends). Weekly SVI for a search term is the number of searches for that term scaled by its time-series average. Figure 1 plots the weekly SVI of two search terms "diet" and "cranberry" during the period from January 2004 to February 2009. The news reference volumes are also plotted in the bottom of the figure. Three interesting observations emerge from this figure. First, SVI does seem to capture public attention. The SVI on "diet" falls during the holiday season and spikes at the beginning of the year. This is consistent with the notion that individuals pay less attention to dieting during the holidays (November and December) but more attention in January when people choose to lose weight as part of their new year's resolutions. The SVI on "cranberry" spikes in November and December, coinciding with the Thanksgiving and Christmas holidays. Second, SVI is able to capture public attention that is not captured by news. While news volume and SVI are correlated, news volume misses out on the beginning-of-the-year spike in attention on "diet" and the December spike in attention on "cranberry." Finally, there is also a large difference in the level of attention in the cross section. For example, "diet" consistently garners more public attention than "cranberry."

We examine a panel of weekly SVI of Russell 3000 stock tickers during our sample period of January 2004 to June 2008. We focus on both the *level* of search frequency and the *change* in search frequency. We compare search frequency to other common proxies of attention and find the

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

following patterns. First, the level of search frequency is positively related to market capitalization, abnormal turnover, analyst coverage and the frequency of news. However, search frequency is not well explained by these proxies of attention. In fact, almost 95 percent of the cross-sectional variation in the *level* of search frequency is not explained by alternative proxies of attention. Second, we find that the *change* in search frequency is significantly related to abnormal return, abnormal turnover and the occurrence of news, but that more than 97 percent of the variation in the *change* in SVI remains unexplained. Overall, these results reinforce the notion that SVI, as a measure of *active* attention, does differ from existing measures of attention. In a vector autoregression (VAR) framework, we find that 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.

Next, we provide evidence that suggests SVI captures the attention of individual investors. Using retail order executions from the SEC Rule 11Ac1-5 (Dash-5) reports, we establish a strong and direct link between SVI changes and trading by individual retail investors. Interestingly, across different market centers, the same increase in SVI leads to much higher individual trading on the market center that typically attracts less sophisticated retail investors (Madoff) than on the market center that attracts more sophisticated retail investors (NYSE for NYSE stocks and Archipelago for NASDAQ stocks). This difference suggests that SVI is likely to capture the attention of more naive individual investors. Trading by the latter investors is more likely to drive prices temporarily away from fundamentals. In addition, since less sophisticated individual investors are more likely to suffer behavioral biases, the prices of stocks they pay attention to and trade will be more affected by behavioral biases.

We then analyze how changes in investor attention measured by changes in SVI are related to stock prices. Individual investors are more prone to search for information when they are buying since they have to choose from a large set of available alternatives, as argued by Barber and Odean (2008). Hirshleifer, Myers, Myers, and Teoh (2008) document consistent evidence that individual investors are net buyers at the time of earnings announcements. This search problem has little impact on selling, since individual investors can only sell what they own. To the extent that an increase in search frequency for a stock measures the increase in individual investor attention demands for that stock, we expect increased buying pressure to follow.

A natural context where such price pressure may occur is during a stock's initial public offering (IPO). Since trading-based attention measures are not available prior to the IPO, SVI offers a unique opportunity to empirically study the impact of retail investor attention on the IPO returns. Ritter and Welch (2002) and Ljungqvist, Nanda and Singh (2006) argue that over-enthusiasm among retail investors may explain high first-day returns and low long-run returns for IPO stocks (Loughran and Ritter, 1995 and 2002). Consistent with their hypothesis, we document that searches relating to IPO stocks increase by more than 40 percent during the IPO week. The jump in SVI indicates a surge in public attention consistent with the marketing role of IPOs documented by Demers and Lewellen (2003). When we compare the group of IPOs that experience large increases in search during the week *prior to* the IPO to the group of IPOs that experience smaller increases in search, we find that the former group outperforms the latter by almost 7 percent during the first day after the IPO and the outperformance is statistically significant. We also document significant long-run return reversals among IPO stocks that experience large increases in search pre-IPO and large first-day returns post-IPO. These patterns are confirmed using cross-sectional regressions. Liu, Sherman and Zhang (2008) recently also find that investor attention measured by newspaper coverage during the filing period prior to the IPO is positively related to the first-day return. Compared to SVI, newspaper coverage is an indirect proxy for investor attention, especially that of the retail investor. This is probably why Liu, Sherman and Zhang (2008) do not find any evidence that the newspaper coverage is related to long-term performance of the IPO.

Among our sample of Russell 3000 stocks, we also find evidence supporting the price pressure hypothesis of Barber and Odean (2008). We find that price pressure operates mainly among Russell 3000 stocks with smaller market capitalization. Within this subset, Russell stocks experiencing large increases in search outperform those experiencing large decreases in search significantly by about 11 basis points per week during the first two weeks – or 5.7 percent per year, which is quite sizable for stocks in the Russell 3000 index. In addition, we document stronger price pressure following a SVI increase among stocks traded mainly by retail investors. Finally, we confirm that the price pressure typically does not persist beyond two weeks and is reverted eventually.

Finally, we analyze how the level of investor attention measured by the SVI is related to stock prices. We focus on attention and the price momentum effect (Jegadeesh and Titman, 1993). The price momentum effect poses the greatest challenge to the traditional asset pricing models. Several behavioral models are proposed to describe the drift patterns of asset prices (Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999). These models differ in the underlying behavioral biases and economic mechanisms they use to generate the momentum effect but investor attention typically plays an important role. As a more direct and higher-frequency measure of investor attention, SVI allows us to conduct a sharper test in distinguishing two behavioral explanations of price momentum.

In the framework of Daniel, Hirshleifer, and Subrahmanyam (1998), investors overreact to private signals and push prices too far relative to fundamentals, causing price momentum. In contrast, in the model of Hong and Stein (1999), information diffuses slowly across investors and is incorporated into prices gradually, resulting in price momentum. Investor attention, measured by SVI, helps to distinguish between these two behavioral explanations. Attention is a necessary condition for overreaction as investors can only overreact to information when they pay attention to a stock (Hou, Peng and Xiong, 2008). Consequently, according to Daniel et al., more attention should lead to more overreaction and thus stronger price momentum. In contrast, as accrued attention typically leads to faster information diffusion, according to Hong and Stein (1999), we would expect weaker momentum among stocks associated with high levels of investor attention.

Following this intuition, we examine the price momentum effect separately among Russell stocks associated with high and low levels of SVI. We study the price momentum effect at the weekly frequency as suggested by Gutierrez and Kelly (2008). Our empirical results support the explanation of Daniel et al. (1998). The price momentum strategy among high-search stocks outperform that among low-search stocks consistently across all holding horizons. The outperformance during a 52-week holding period is almost 2.5 percent which is statistically significant and survives characteristic adjustment (Daniel, Grinblatt, Titman, and Wermers, 1997). There are two reasons why more Google search, combined with investor overconfidence, may result in a stronger price momentum. First, many psychological studies find that people feel more confident when they have more information or expertise (See Gilovich, Griffin and Kahneman, 2002). As investor attention is drawn to a stock, they may feel that they have more expertise and thus become more overconfident about it. Second, after searching for a stock in Google, investors are often led to the same information sets so that their private signals are more correlated. In turn, this will generate a stronger price momentum according to the model of Daniel et al. (1998).

The rest of the paper is organized as follows. Section 2 describes data sources and how we construct our aggregate Google search volume index (SVI) variable. Section 3 compares our SVI measure to alternative proxies of investor attention and examines additional factors that drive our SVI measure. Section 4 provides direct evidence that SVI captures the attention of individual investors. Section 5 analyzes how changes in investor attention measured by changes in SVI relate to stock prices. Section 6 analyzes how the level of investor attention measured by the level of SVI is related to prices and, in particular, the price momentum effect. Finally, Section 7 concludes.

2 Data and Sample Construction

Google Trends provides data on search term frequency dating back to January 2004. For our analysis, we download the weekly search volume index (SVI) for individual stocks. To make the data collection and cleaning task manageable, we focus on stocks in the Russell 3000 index for most of the paper. The Russell 3000 index contains the 3,000 largest companies, representing more than 90 percent of the total U.S. equity market capitalization. As Russell 3000 stocks are relatively large stocks, our results are less likely to be affected by bid-ask bounce and other market microstructure related issues. We obtain the membership of Russell 3000 index directly from Frank Russell and Company. To minimize survivorship bias, we include all 3,606 stocks that were ever included in the index during our sampling period from January 2004 to June 2008. For our empirical analysis, we exclude stocks with a market price of less than five dollars.

Our next empirical choice concerned 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 three reasons. First, investors may search the company name for reasons unrelated to investing. For example, one may search "Best Buy" in order to do online shopping rather than to collect financial information about the firm. This problem is more severe if the company name has multiple meanings (e.g. "Apple" or "Amazon"). Second, Google Trends does not allow non-alphabetical terms, so search data on companies such as "3M" and "7-Eleven" will be missing. Finally, 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 much less ambiguous. If an investor is searching "AAPL" (the ticker for Apple Inc.) in Google, it is clear that she is interested in the financial information about the stock of Apple Inc. Since a firm's ticker is always alphabetical and uniquely assigned, identifying a stock using its ticker also avoids the other two problems associated with using company 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 also cautious about using the ticker if it has a generic meaning such as "GPS", "DNA", "BABY", "A", "B", and "ALL". We manually go through all the Russell stock tickers in our sample and flag such "noisy" tickers. These tickers are usually associated with abnormally high SVIs that may have nothing to do with investor attention to the stocks with these ticker symbols. Not surprisingly, when we exclude these "noisy" tickers (about 7 percent of our sample), our results typically become stronger.

To facilitate cross-sectional comparison, we make use of the feature in Google Trends which allows us to conduct a search of two terms simultaneously (as in the "diet" and "cranberry" example) so that the two SVI time series will both be normalized by the same constant: the time-series average of the first search item ("diet" in this case). This allows for cross-sectional comparison. In our study, we run comparative searches with the Microsoft ticker "MSFT." This way each firm's SVI will be scaled by the same constant: the average weekly SVI of MSFT. Any reference ticker can be chosen: to select an alternate reference ticker would apply a different constant scaling factor to SVI, but would not affect the analysis. To compare the search frequency for Apple's ticker AAPL with MSFT we input "MSFT, AAPL" into Google Trends. The graphical output is displayed in Panel B of Figure 1. Two interesting observations emerge from this figure. First, we observe spikes in the SVI of "AAPL" in the beginning of a year. These spikes may be capturing increasing public attention coming from (1) the MacWorld conference which is held during the first week of January and (2) awareness of the company after receiving Apple products as holiday gifts. Second, it is worth noting that although Microsoft has a larger market capitalization, more media coverage and more trading volume than Apple, AAPL is searched more than twice as often as MSFT. These two observations again support our argument that SVI indeed captures investor attention and is different from existing proxies of attention.

To collect data on all stocks in the Russell 3000, we employ a webcrawling program that inputs each ticker and "MSFT" into Google Trends and uses the Google Trends' option to download the SVI data into a CSV file. We do this for all 3,606 stocks in our sample. This generates a total of 487,084 firm-week observations. Unfortunately, Google Trends does not return a valid SVI for some of our queries. If a ticker is searched too seldom or too often (relative to "MSFT"), Google Trends will return a 0 value for that ticker's SVI. Of our 487,084 firm-week observations, 381,106 have valid (non-zero) SVI.

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

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

We obtain the original SEC Rule 11Ac1-5 (Dash-5) monthly reports from Market System Incorporated, which aggregates the monthly Dash-5 reports provided by participating market centers and provides various transaction cost and execution quality statistics based on the Dash-5 data.

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

3 What Drives SVI?

In this section, we examine what drives SVI and compare SVI to other common proxies of attention. The variables of interest include the following: *Log(Market Capitalization)* is the natural logarithm of market capitalization;*Absolute Abnormal Return* is the absolute value of the concurrent week DGTW abnormal return; *Abnormal Turnover* is the standardized abnormal turnover as in Chordia, Huh and Subrahmanyam, 2007; *News Dummy* is a dummy variable which takes the value 1 if there is a news story in the Dow Jones news archive in the concurrent week; *Chunky News Dummy* is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive; *Log(1+Number of Analysts)* is the natural logarithm of the number of analysts in I/B/E/S; *Advertising Expense / Sales* is the ratio between the advertising expense and sales in the previous fiscal year and *Log(Chunky News Last Year)* is the natural logarithm of the number of Chunky News stories in the last 52 weeks.

Table 1 presents the contemporaneous correlations among various measures of attention. As one would expect, SVI is positively correlated with several existing proxies of attention. For example, stocks that experience more Google searches are on average larger stocks with more news coverage and events, more coverage from analysts and more trading volume. The correlation between SVI and the advertising expense variable is close to zero, which may not be too surprising since the advertising expense variable is only available at an annual frequency and is scaled by sales. Absolute Abnormal Return, which is also closely related to volatility, should be lower for large stocks. As a result, it is negatively correlated to SVI given the strong positive correlation between SVI and the size of the stock. Interestingly, the correlation between SVI and alternative proxies of attention is quite low at the weekly frequency, highlighting the distinct feature of SVI in capturing the *demand* for attention or *active* attention.

We next examine the relation between the *level* of SVI and other proxies of attention in a set of regressions. The results are reported in Table 2 where the dependent variable is the natural logarithm of SVI. All regressions reported in this table contain week fixed-effects, and the standard errors are clustered by firm. We confirm that the level of SVI is positively related to both the size of the stock and the abnormal turnover. Comparing regressions 1 and 2, we find that the *Chunky News Dummy* is more important in driving the level of SVI than the *News Dummy*, suggesting that the occurrence of news (rather than news coverage) matters. The regression coefficient on *Log(Chunky News Last Year) is* also positive and significant, suggesting that past occurrences of news also matter. Regressions 3 to 5 all find a negative coefficient on the analyst coverage variable, which is part driven by the large positive correlation (0.77) between the size of the stock and analyst coverage. Finally, the R-squared of these regressions are only about 5 percent, suggesting that existing proxies of attention only explain a small fraction of the variation in the level of SVI. Regression 5 contains most alternative proxies of attention. Later we will use this specification to create *Residual SVI* which is, by construction, orthogonal to existing attention proxies.

The change in investor attention over time is also of interest. To measure such change, we define the SVI_Change variable as:

$$SVI\_Change_t = \log(SVI_t) - \log[Med(SVI_{t-1}, ..., SVI_{t-8})], \tag{1}$$

where $\log(SVI_t)$ is the logarithm of SVI during week t, and $\log[Med(SVI_{t-1}, ..., SVI_{t-8})]$ is the logarithm of the median value of SVI during the prior eight weeks. As we rarely observe a negative shock to investor attention, SVI_Change_t well captures the surge in attention during the current week. In addition, as attention returns to its normal level after a positive jump, this change, under the current definition, will not be misclassfied as a negative shock to attention.

We regress SVI_Change on other proxies of attention in a similar set of regressions. The results are reported in Table 3. When we focus on changes, *Absolute Abnormal Return* and *Abnormal Turnover* become strongly related to SVI_Change. Consistent with the result in Table 2, *Chunky News Dummy* (news occurrence), not *News Dummy* (news coverage), is positively and significantly related to changes in SVI. In addition, Chunky News in the last 52 weeks is also correlated with changes in SVI. Overall, much of the variation in SVI change remains unexplained with a regression R-Squared of about 2.8 percent. The residual from regression (5), labeled *Residual SVI Change*, is by construction orthogonal to existing attention proxies.[3]

We examine the weekly lead-lag relation among measure and proxies of attention using a vector autoregression (VAR). For this exercise, we only include variables that are observable at weekly fre-

[3]We have also computed *Residual SVI* and *Residual SVI Change* after including several lagged variables such as the lagged stock return and the lagged turnover in regression (5). The control for lagged variables hardly changes the results in the rest of our paper.

quencies. The four variables include *Log(SVI)*, the natural logarithm of weekly SVI; *Log(turnover)*, the natural logarithm of weekly turnover; *Absolute Abnormal Return*, the absolute value of the concurrent week DGTW abnormal return; and *Log(1+Chunky News)*, the natural logarithm of one plus the number of chunky news during that week. We run the VAR for each stock with at least two years of weekly data. We include both a constant and a time trend in the VAR. The VAR coefficients are then averaged across stocks and reported in Table 4.

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

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

4 SVI and Individual Investors

Whose attention is captured with SVI? Intuitively, people who search financial information related to a stock in Google are more likely to be individual or retail investors since institutional investors have access to more sophisticated information services such as Reuters or Bloomberg.[4] In this section, we provide direct evidence that changes in investor attention measured by SVI are indeed

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

related to trading by individual investors. For investor attention to affect stock price, it is crucial to first establish this link between attention and individual trading.

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

Instead, we obtain retail orders and trades directly from Dash-5 monthly reports. Since 2001, SEC Rule 11Ac1-5 and the subsequent Regulation 605 required every market center to make public monthly reports of statistical information concerning the "covered orders" they received for execution. The "covered orders" primarily come from individual / retail investors because they exclude any orders for which the customer requests special handling for execution. There should be few institutional orders because institutions typically use so-called "not-held-orders" which are precluded from the Dash-5 reporting requirement. In addition, all order sizes greater than 10,000 shares are not presented in the Dash-5 data. This further reduces the likelihood of having any institutional orders in the Dash-5 data.[5]

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

The main advantage of the Dash-5 reports for our study is that they provide direct information on trading by individual investors. However, there are a few limitations associated with Dash-5 reports. First, Dash-5 reports may exclude large retail orders placed by individual investors. Second, Dash-5 reports are not audited and may be sensitive to alternative ways of aggregating the

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

underlying order data. However, Boehmer, Jennings and Wei (2007) find no evidence of systematic inaccuracies in Dash-5 reports. Finally, Dash-5 data are only available at a monthly frequency.

Despite these limitations, 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 SVIs in Table 5. The monthly SVI is computed by linear interpolation of weekly SVI to daily SVI before aggregating them for each calendar month. We consider several alternative proxies of attention as control variables: *Log(Market Cap)* is the logarithm of the prior month-end (t-1) market capitalization; *RET(t)* is the monthly return from the current month (t); $|RET(t)|$ is the absolute value of the return of the stock during month (t); *Chunky News Dummy* is equal to one if there is at least one chunky news story in the Dow Jones News archive during month (t) and zero otherwise; and *Advert. Expense/Sales* is the latest advertisement expenditure to sales ratio available from COMPUSTAT prior to month (t), where we set advertisement expenditure equal to zero if advertisement expenditure is missing.

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

In Panel A of Table 5, we examine the changes in individual trading across all markets centers. Initially, we first consider the first two order size categories (100 – 1,999 shares) in the Dash-5 reports. This choice is consistent with prior literature. As Lee and Radhakrishna (2000) point out, a trade size of $20,000 is a reasonable cutoff value for a typical retail investor's trade size. In our sample, the median stock price per share is about $24, which corresponds to an average trade size of about 1,000 shares. When we measure changes in individual trading as changes in the number of orders (in logarithm), we find that a 1 percent increase in the SVI leads to 0.062 percent increase in individual orders (regression 1). This positive correlation is statistically significant at the 1 percent level despite the fact that we have controlled for alternative proxies of attention and other trading-related stock characteristics. It is not too surprising that several alternative proxies of attention are also significant since they might be mechanically related to trading. For example, trading can correlate with absolute returns or market capitalizations via price impact, and trading can correlate with news if news coverage is triggered by abnormal trading. In regression 2, we measure changes in individual trading by changes in turnover (in logarithm) and find an even stronger relation between the change in individual trading and the change in SVI.

Ultimately, we use all order size categories (100 – 9,999 shares) in the Dash-5 reports. We find almost identical results as reported in regressions 3 and 4 in Panel A of Table 5. In fact, unreported analysis produces very similar results when we use order size category 100 – 499 shares or order size category 100 - 4999 shares, which leads us to believe that our conclusion is robust to finer definitions of retail trading. Without introducing additional subjectivity in our study, we choose to include orders of all sizes reported in Dash-5 (100 – 9999 shares) for the remaining part of our analysis.

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

We repeat our regressions separately for Madoff and NYSE/Archipelago in Panel B of Table 5. Interestingly, we find the correlation between the change in individual trading and the change in SVI is much stronger at Madoff. After controlling for alternative proxies of attention and other trading-related stock characteristics, a 1 percent increase in SVI translates to a 0.181 percent increase in individual orders and a 0.191 percent increase in individual turnover at Madoff (regressions 1 and 2). Such 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 0.060 percent and 0.094 percent). In contrast, the same 1 percent increase in SVI only translates to a 0.054 percent increase in individual orders and a 0.083 percent increase in individual turnover at NYSE/Archipelago (regressions 3 and 4). Finally, we directly examine the difference in retail trading between Madoff and NYSE/Archipelago using a matched sample in regressions 5 and 6. Each month, we focus on a set of stocks that are traded on both Madoff and NYSE/Archipelago. We create a dummy variable *Madoff* which takes value the value one for all observations from Madoff and zero for all observations from NYSE/Archipelago. In this matched sample, we find that a 1 percent increase in SVI leads to a 0.102 percent greater increase in individual orders and a 0.054 percent greater increase in individual turnover at Madoff and these additional increases are statistically significant.

In sum, our results suggest that SVI captures the attention of less sophisticated individual investors.

5 Changes in SVI and Stock Prices

As seen from Figure 1, atention can vary considerably over time. How do such changes in attention affect stock returns? This is the question that we examine in this section. Barber and Odean (2008) argue that individual investors are more likely to search for information and thus pay attention when they are buying since they have to choose from a large set of available alternatives. This search problem has little impact on selling, since individual investors can only sell what they own. To the extent that a large positive SVI_Change_t measures increases in individual investor attention, we expect increased buying pressure to subsequently push up stock prices temporarily. We first examine such price pressure in the context of IPOs. Given the lack of trading data prior to the IPO, SVI offers a unique opportunity to empirically study the impact of retail investor attention on IPO returns.

5.1 IPO Stock Sample

There are two main stylized facts about IPO returns. First, IPOs on average have large first-day returns (see Loughran and Ritter, 2002). Second, IPOs exhibit heterogeneous long-run performance, while small-growth IPOs underperform non-IPO seasoned companies (Loughran and Ritter, 1995).

Ljungqvist, Nanda and Singh (2006) and Ritter and Welch (2002) conjecture that the over-enthusiasm of retail investors may drive up an IPO's first-day return, and eventually overpriced IPOs revert to fundamental value which causes long-run underperformance. There are some circumstances in which researchers have been able to obtain the pre-IPO valuation of retail investors as a measure of retail investor sentiment. For example, using a novel dataset on the 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 the first-day IPO return, and negatively correlated with IPO performance up to one year after going public.

We take a different route to test such conjectures. For the investor to become overly enthusiastic about a forthcoming IPO, he must allocate attention to the equity issuance. If there is no attention from retail investors in the first place, then these retail investors are less likely to affect the first-day return and long-run performance of the IPO. In order to test the hypothesis of Ritter and Welch (2002), the main empirical challenge is to identify investors' stock-specific attention prior to the IPO.

In this subsection, we use the change in SVI (SVI_Change) as our measure of investor attention prior to the IPO. Because there is no ticker widely available prior to the IPO, we use the company name provided by the Security Data Corporation (SDC) to search for the stock in Google Trends in order to obtain the SVI. As in the case of using tickers, to facilitate cross-sectional comparison, we choose a benchmark to be Hoku Scientific, Inc (keyword search: Hoku; and NASDAQ ticker symbol: HOKU), one of the IPOs in our sample with a median offering size at the time of IPO. For the sample of IPOs from 2004 to 2007, we are able to identify 181 IPOs with valid SVIs.[6]

First, we 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 level of the SVI around the IPO week (week 0). We observe a significant upward trend in SVI starting two to three weeks prior to the IPO week, and there is a significant jump in SVI during the IPO week. The median SVI is much lower than the mean SVI, indicating positive skewness in the cross-sectional distribution of SVI. Panel B of Figure 2 confirms the pattern using changes in SVI around the IPO week. The SVI on an IPO stock jumps by 80 percent (using the median) during the IPO week, reflecting a surge in public attention toward the stock. Interestingly, the shift in attention is not permanent. The SVI reverts to its pre-IPO level two weeks after the IPO.

Second, we examine the relation between increased attention prior to the IPO and the first-day IPO return. Panel A of Figure 3 summarizes the main results. Consistent with Ritter and Welch's conjecture, the set of IPOs with low SVI_Change during the week prior to the IPO have first-day returns of 10.48 percent on average while the set of IPOs with high SVI_Change have much higher first-day return of 17.25 percent on average. The difference between the two average first-day returns is about 6.78 percent. Both t-tests and nonparametric Wilcoxon tests indicate that the difference is statistically significant at the 1 percent level.

We formalize the analysis using cross-sectional regressions in Table 6. In regression 1, we regress the IPO's first-day return against SVI_Change. In regression 2, we also control for other variables that may have predictive power for first-day IPO returns. These variables include offering price revisions, defined as the ratio of the offering price to the medium filing price; the logarithm of offering size, defined as the number of shares offered times the offering price; the cumulative industry return six month prior to the offering to the end of month prior to te IPO. In these two regressions, SVI_Change is statistically significant at the 5 percent level. Comparing these two regressions, it is clear that pre-IPO investor attention measured by SVI plays an important role in

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

determining the first-day IPO return, though its impact attenuates in the presence of offering price revisions which may capture and aggregate institutional investor demand.

Third, we examine the relation between increased attention prior to the IPO and the long-run performance of the IPO stock. Panel B of Figure 3 summarizes the main findings. The figure plots the mean and median of the industry-adjusted cumulative IPO returns, starting at the beginning of the fourth month after the IPO and ending at the end of the twelfth month after the IPO. We skip the first three months after the IPO due to 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). We focus on the IPOs that experience large first-day returns and further divide them into two portfolios based on changes in their SVI prior to the IPO. This figure illustrates that IPOs with large first-day returns driven by investor attention indeed underperform average firms in the same industry over the long run. In contrast, IPOs experiencing large first-day returns without large increases in their SVI prior to IPO do not experience long-run reversal.

We formalize the analysis using cross-sectional regressions in Table 7 where we include additional control variables. We find that neither SVI_Change nor first-day Return alone predict long-run IPO underperformance. Interestingly, the interaction between SVI_Change and first-day Return does. This is consistent with our conjecture that for IPOs with high first-day returns that also experienced increases in investor attention, the high first-day returns are partly driven by "price pressure" and will revert in the long run. In addition, the interaction term between the first-day return and the offering price revision is not significant in the regressions. As we have shown, SVI more likely captures the attention of individual retail investors while offering price revisions capture the attention of institutional investors. The insignificance of the offering price revision variable confirms that it is the individual investor's attention that contributes to the high first-day IPO return which is eventually reversed in the long-run.

In a related study, Liu, Sherman and Zhang (2008) find that newspaper article counts during the filing period prior to the IPO are positively related to the first-day return, conditional on upward revision of offering price to the initial filing price. They do not find any evidence that news article counts are related to long-term performance of the IPO. Print media's coverage of IPO during the filing period is sporadic. In fact, in their sample, the median number of news articles per month is about 1.5 articles, or about 3 articles throughout the filing period. Tetlock (2008) points out that, investor overreaction mainly comes from repeated media coverage of stale news. Therefore, print media coverage by itself may not attract enough attention from retail investors. Consistent with this view, Liu et al. (2008) interpret newspaper article counts to reflect the demand "from genuine (as opposed to temporary, sentiment-driven) investors." In contrast, the pre-IPO SVI change is likely to serve as a direct measure of retail investor attention.

5.2 Russell 3000 Stock Sample

We then investigate the empirical relation between changes in SVI and future stock returns in general for all Russell 3000 stocks in our sample.

We first conduct our analysis using a portfolio-based approach. Specifically, each week during our sampling period from January 2004 to June 2008, we first sort Russell 3000 stocks in our sample based on their market capitalizations into three groups. Within the large (top 1/3) and small (bottom 1/3) Russell stock groups, we then sort stocks based on their SVI_Change in that week into five portfolios. Average future portfolio returns during the next four weeks are reported in Panel A of Table 8. We report both the raw returns and the DGTW characteristics-adjusted returns which control for size, book-to-market and past return characteristics (see Daniel et al., 1997). The t-values associated with spread portfolio returns are computed using the Newey-West formula with the lag equal to the number of overlapping months in the average return calculation.

Panel A reports significant positive returns during the first two weeks following an increase in SVI but only among smaller Russell stocks, consistent with our conjecture that these positive returns are driven by price pressure which should be more prominent among small stocks. Among the smaller Russell 3000 stocks, those experiencing large SVI_Change outperform those experience small or negative SVI_Change by about 11 basis points per week during the first two weeks. This outperformance translates to an annualized return of almost 5.7 percent, which is quite sizable for Russell stocks.[7] In addition, the DGTW characteristic-adjustment makes the outperformance only stronger. Over time, the initial outperformance stops after two weeks and unreported results suggest that it is completely reversed within the first year after portfolio formation.

We also replace SVI_Change with the Residual SVI change computed using regression (5) in

[7] This does not immediately translate to a profitable trading strategy for two reasons. First, we have not accounted for the transaction costs. Second, the SVI is made available to the general public only after January 2008.

Table 3. In addition, we exclude all Russell stocks with "noisy" tickers discussed in Section 2. We then repeat the portfolio exercise and report the results in Panel B of Table 8. The results are very similar to those in Panel A, which confirms that our results are not driven by SVI's correlations with alternative proxies of attention.

When we examine long-horizon returns in Table 8, we find that over a 26-week-period, stocks experiencing large SVI_Change do not significantly outperform those experience small or negative SVI_Change. In fact, they underperform (again not significantly) in several cases. The long-horizon returns suggest that the initial positive price reaction during the first two weeks following a SVI increase more likely reflects a temporary price pressure due to increase retail attention, rather than a permanent price impact due to the arrival of new information.

Second, we repeat the analysis using panel regressions and report the results in Table 9. The dependent variables are the DGTW abnormal returns during each of the next four weeks and the independent variables are SVI_Change and alternative proxies of attention. Confirming our results from the portfolio-based approach, SVI_Change positively and significantly predicts returns over the next two weeks even with the presence of alternative attention proxies. In addition, the predictive power of SVI_Change is stronger among smaller stocks, reflected in a negative and significant coefficient on the interaction term between SVI_Change and log (Market Cap). Finally, the regression analysis allows us to interact SVI_Change with retail trading. We measure the degree of retailing trading using $Percent\ Dash\text{-}5\ Volume$, which is defined as the ratio between Dash-5 trading volume and the total trading volume during the previous month. We find the interaction between this retail trading measure and SVI_Change is highly significant in predicting the first-week abnormal stock return, which suggests stronger price pressure among stocks traded mainly by retail investors. Overall, our results support the price pressure hypothesis of Barber and Odean (2008): when retail investors pay more attention to a stock, they are more likely to buy it and push up its price temporarily.

6 Levels of SVI and Stock Prices

Figure 1 also shows that different stocks may receive very different levels of attention. In this section, we analyze how the levels of investor attention measured by the levels of SVI are related to stock prices. Here we zoom into the price momentum effect (Jegadeesh and Titman, 1993), which presents the biggest challenge to rational asset pricing models. Two prominent behavioral explanations are offered in the literature. The mechanisms that generate price momentum are quite different across these two explanations. In the framework of Daniel, Hirshleifer, and Subrahmanyam (1998), investors overreact to private signals and push prices too far relative to fundamentals, causing price momentum. In contrast, in the model of Hong and Stein (1999), information diffuses slowly across investors and is incorporated into prices gradually, leading to price momentum.

Investor attention, measured by the level of SVI, turns out to be an interesting instrument that helps to distinguish these two behavioral explanations. Attention is a necessary condition for overreaction as investors can only overreact to information when they pay attention to a stock (Hou, Peng and Xiong, 2008). Consequently, according to Daniel et al. (1998), more attention should lead to more overreaction and thus stronger price momentum. In contrast, as more attention typically leads to faster information diffusion, according to Hong and Stein (1999), we would expect weaker momentum among stocks associated with high levels of investor attention.

Motivated by this intuition, we examine the price momentum effect separately among Russell stocks associated with high and low levels of SVI. We study the price momentum effect using the weekly return There are several advantages of using weekly return in our context. First, there is a pervasive momentum effect in the weekly return (Gutierrez and Kelly, 2008). Second, weekly return matches the frequency of the SVI data available to us. Third, since our sample is relatively short, conducting asset pricing tests at the weekly frequency increases the statistical power. Lastly and most importantly, according to Gutierrez and Kelly (2008), weekly return constitutes "a new, and arguably superior, testing ground" for assessing potential explanations of momentum since it "affords researchers greater confidence in identifying the news that underlines the return."

We first adopt a portfolio-based approach. Specifically, each week during our sampling period from January 2004 to June 2008, we first sort Russell 3000 stocks in our sample based on their level of SVI into 5 groups. Within each group, we then sort the stocks further into 5 portfolios based on their returns during the week. Stocks in the highest return portfolio are the winners, and stocks in the lowest return portfolio are the losers. In Panel A of Table 10, we report the returns to the momentum strategies of buying winners and selling losers for the highest-SVI stock group and the lowest-SVI stock group. We report both the raw returns and the DGTW characteristics-adjusted returns which control for size, book-to-market and past return characteristics. The t-values associated with spread portfolio returns are computed using the Newey-West formula with the lag equal to the number of overlapping months used in the average return calculation. The results in Panel A suggest that the price momentum strategy works much better among stocks associated with a high level of investor attention. The price momentum strategy among the high-SVI stocks outperforms that among low-SVI stocks consistently across all holding horizons. With an annual holding horizon, a momentum strategy returns about 2.45 percent more among high-SVI stocks (t-value = 2.73). Results are very similar with the DGTW characteristic-adjusted returns. Since the characteristic-adjusted return controls for past one-year performance of the stock, the higher price momentum profit among the high-SVI stocks is clearly not because we are loading on extreme past winners or losers. These empirical results support the explanation offered by Daniel, Hirshleifer, and Subrahmanyam (1998) and are less consistent with the prediction of Hong and Stein (1999). There are two reasons why Google search, combined with investor overconfidence, may result in a stronger price momentum. First, many psychological studies find that people feel more confident when they have more information or expertise (see Gilovich, Griffin and Kahneman, 2002). As the attention of these investors is drawn to a stock, they may feel that they have more expertise and thus become overconfident. Second, after searching for a stock in Google, investors are often led to the same information sets so that their private signals are correlated.[8] In turn, this will generate stronger price momentum according to the model of Daniel et al. (1998).[9] Given the relatively short sampling period, we are not able to examine the long-run return reversals on our momentum portfolios.

Of course, higher price momentum could be driven by other stock characteristics correlated with SVI. To understand our results better, we report average stock characteristics for momentum portfolios for both high-SVI and low-SVI groups in Panel B of Table 10. Several interesting observations can be made here. First, ThisWeek_Ret_Diff variable, measuring the winner-minus-loser return during the current week, is in fact higher in the low-SVI group, which means that the high price momentum we observe in the high-SVI group is not driven by investing in stocks with more

[8] For a similar argument using analyst forecasts, see Hwang (2009).

[9] If individual investor attention and related overconfidence are driving price momentum, we would expect them to impact past winners more since individual investors have to possess past losers to sell them (given such investors rarely short sell). Unreported results indeed suggest that the larger price momentum among high-SVI stocks mainly comes from price continuation among past winners rather than past losers.

extreme past returns. Second, high-SVI stocks are bigger, which suggests that their high price momentum returns are not driven by small stocks.

Hong, Lim and Stein (2000) provide empirical evidence supporting the slow information diffusion explanation of price momentum as suggested in Hong and Stein (1999). In particular, they document a higher price momentum effect among stocks receiving less analyst coverage where information likely diffuses slowly. Such slow information diffusion associated with low analyst coverage cannot explain the stronger price momentum effect among high-SVI stocks. Panel B of Table 10 suggests that high-SVI stocks actually receive significantly higher analyst coverage. This should not surprise us since high-SVI stocks are also bigger. More directly, we conduct a 5 by 5 double sort of Russell 3000 stocks on analyst coverage first and current-return second and examine the momentum profit among high- and low-analyst-coverage stocks. The results in Panel C of Table 10 suggest that our weekly momentum strategy performs very similarly among high- and low-analyst-coverage stocks. In fact, low-analyst coverage stocks, smaller on average, actually experience a stronger short-term return reversal. Overall, our results indicate that the slow information diffusion as suggested by Hong and Stein (1999) does not drive the price momentum effect at least during our sampling period among Russell 3000 stocks.

Panel B of Table 10 shows that SVI is positively correlated with other proxies of attention such as turnover, news and advertising expense. To ensure that our result is not driven by SVI's correlations with these alternative proxies, we conduct two more tests. In the first test, we repeat the portfolio exercise after replacing SVI with the Residual SVI computed using regression 5 in Table 2. We also exclude all Russell stocks with "noisy" tickers discussed in Section 2. The results reported in Panel D of Table 10 lead us to draw the same conclusion. The difference between profits to momentum strategies implemented in high- and low-SVI groups is slightly smaller but is still significant if the holding horizon is equal or longer than26 weeks. In the second test, we repeat the analysis using panel regressions and report the results in Table 11. The dependent variables in the regressions are the DGTW cumulative abnormal returns for different holding horizons up to a year (52 weeks). The independent variables are Return in the current week interacted with SVI or alternative proxies of attention. Confirming our results from the portfolio-based approach, the interaction between the current week return and SVI significantly predict long-term stock returns even with the presence of alternative attention proxies.

7 Conclusion

In this paper, we make several contributions to the literature on investor attention and asset prices. First, we propose a novel measure of investor attention using aggregate search frequency in Google (SVI), which is inexpensive and readily available in real-time. We provide strong empirical evidence that SVI captures the *active* attention of retail investors. Second, we provide some initial evidence on the determinants of SVI in both the time-series and cross-section. Trading volume, extreme returns, news and media coverage are related to SVI but only explain a small fraction of its variation. Combined with the fact that SVI predicts most other attention measures, this suggests that SVI uniquely – and more effectively – measures individual investors' attention. Third, we are able to directly relate changes in SVI to the trading behavior of individual investors. This provides confirming evidence that our measure of attention indeed measures the attention of individuals who are perhaps less sophisticated. This tells us what type of attention we are capturing with SVI and motivates many of our tests which relate attention and asset prices. Equipped with this direct measure of retail investor attention, we find strong evidence that increases in SVI temporarily push up stock prices, especially in the context of an IPO. We also document stronger price momentum among stocks with high SVI, which supports the explanation of momentum effect proposed by Daniel, Hirshleifer and Subrahmanyam (1998).

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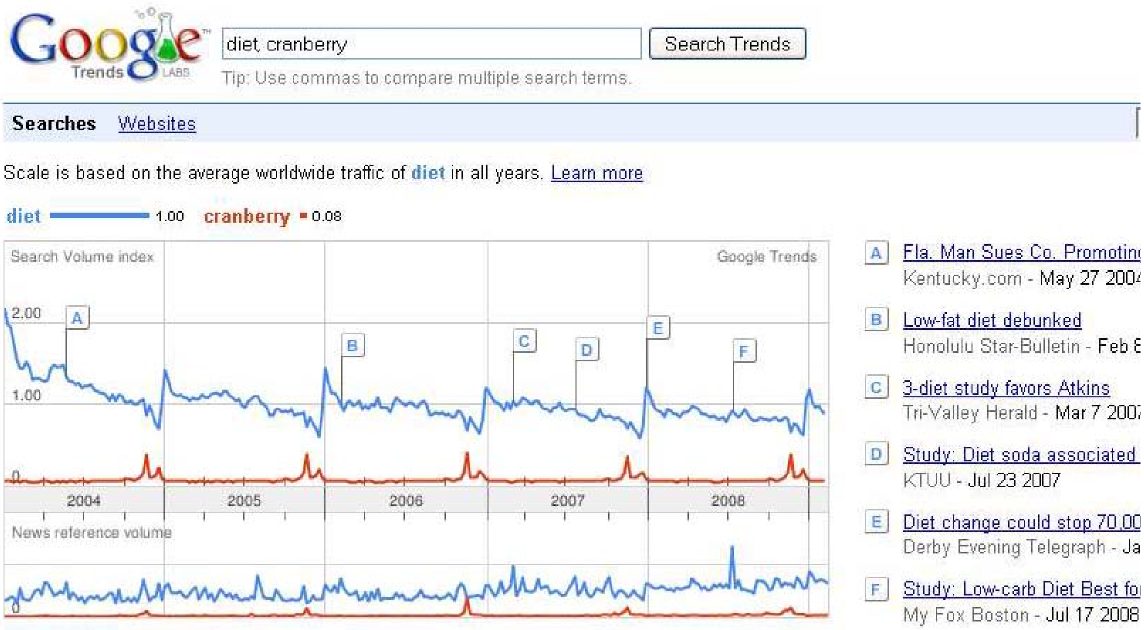
Figure 1: Illustrations of Google Trends Search

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

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



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

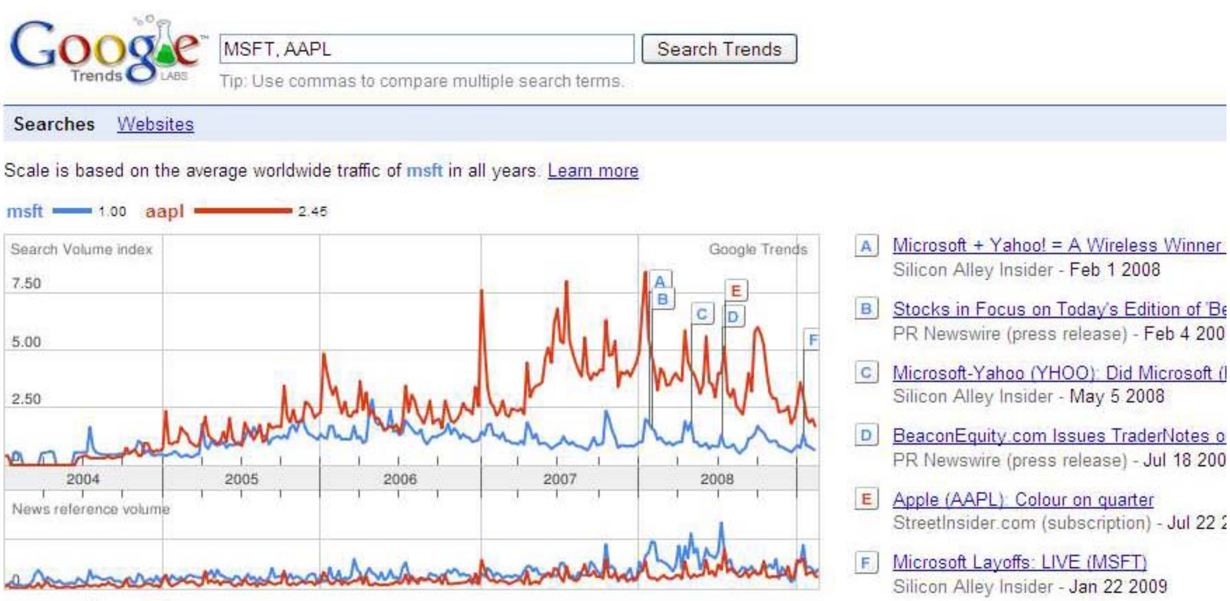
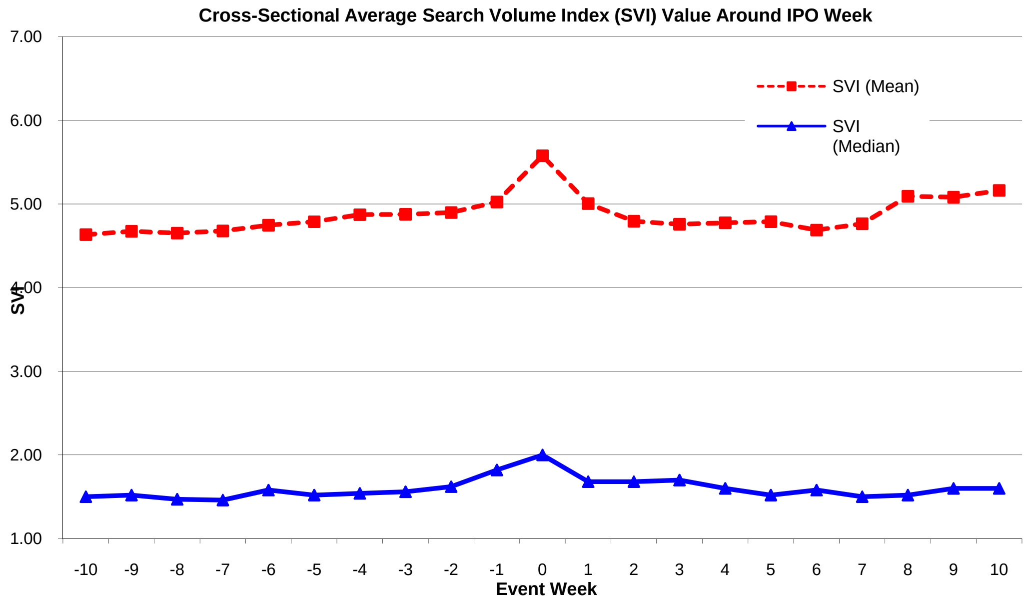


Figure 2: Average *Level* of SVI and *Change* in SVI around IPO

Panel A plots the cross-sectional mean and median of the SVI around the week of initial public offering (IPO). Panel B plots the cross-sectional mean and median of the SVI changes (SVI_Change) around the week of IPO. Week 0 is the week of the IPO. The sample period is from January 2004 to December 2007. There are 181 IPOs with valid SVI in this sample.

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



Panel B: Cross-sectional Average SVI Changes around IPO

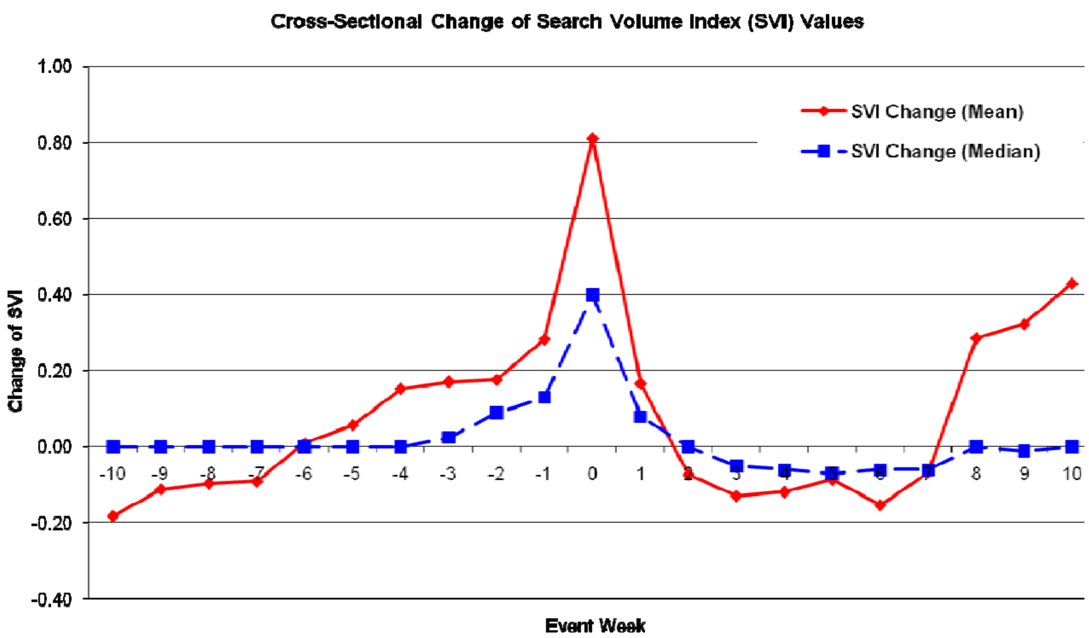
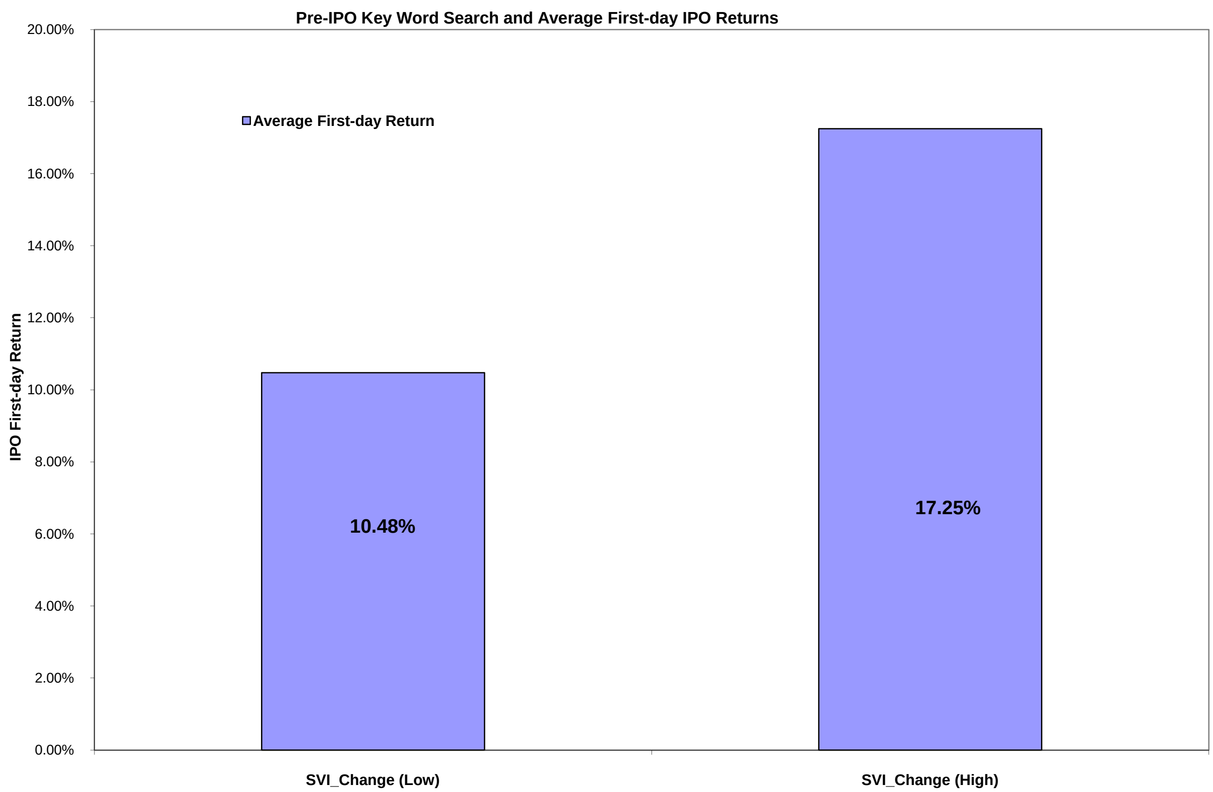


Figure 3: Pre-IPO SVI Changes, Average First-day IPO Returns and Long-Run IPO Returns

Panel A plots the pre-IPO SVI changes and average first-day returns. Panel B plots the pre-IPO SVI changes and the Fama-French 48-industry adjusted cumulative abnormal returns from the fourth month to the twelfth month. The sample period is from January, 2004 to December, 2007. There are 181 IPOs with valid SVI in this sample.

Panel A: Pre-IPO SVI Changes and Average First-day IPO Returns



Panel B: Pre-IPO SVI Changes and Cross-Sectional Average of Industry Adjusted IPO Cumulative Returns (4 to 12 months)

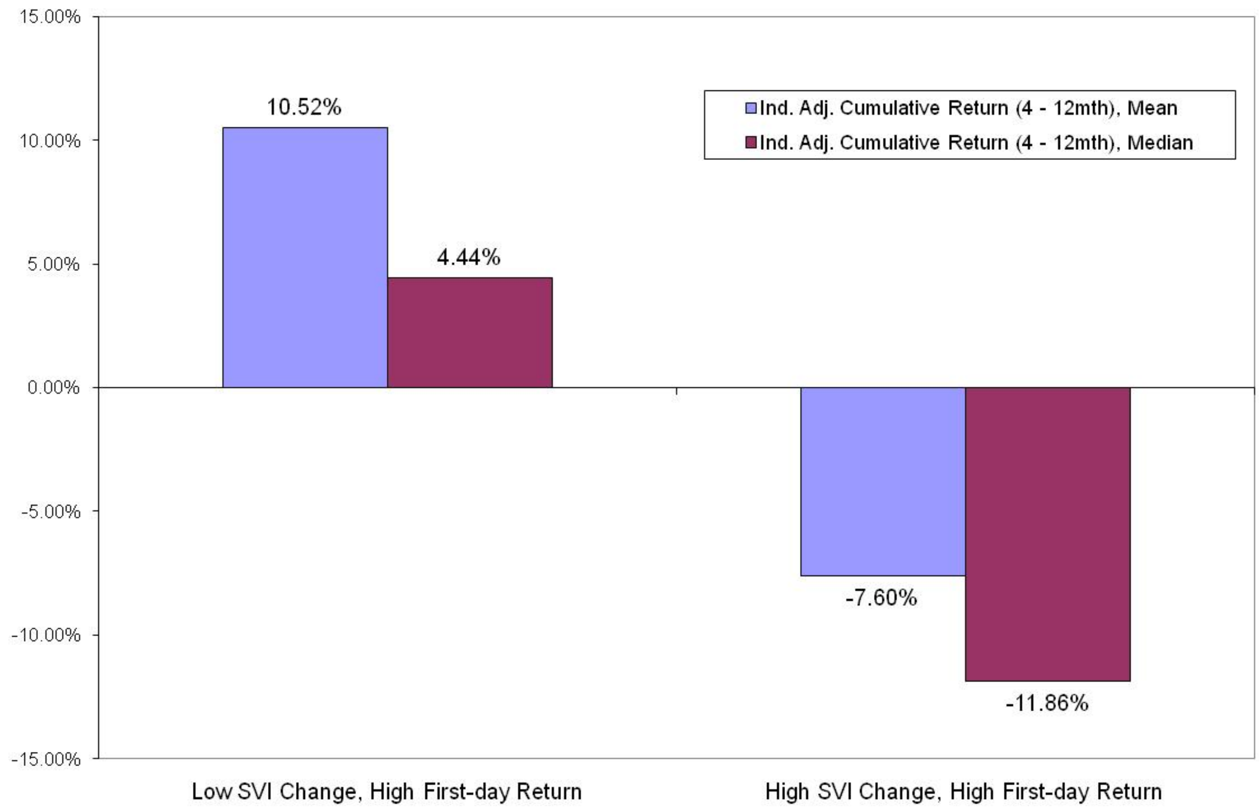


Table 1: Correlation among Measures of Attention

SVI is the aggregate search frequency from Google Trends. Log(Market Capitalization) is the natural logarithm of market capitalization; Absolute Abnormal return is the absolute value of the concurrent week DGTW abnormal return; Abnormal Turnover is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007); News Dummy is a dummy variable which takes the value 1 if there is a news story in the Dow Jones news archive in the concurrent week; Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive in the concurrent week; Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S; Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last 52 weeks; and Advertising Expense / Sales is the ratio between the advertising expense and sales in the previous fiscal year. The sample period is from January 2004 to June 2008.

	Log(SVI)	Log (Market Cap)	Absolute Abnormal Return	Abnormal Turnover	News Dummy	Chunky News Dummy	Log(1+# of Analysts)	Log (Chunky News Last Year)	Advert. Expense / Sales
Log(SVI)	1.00	0.15	-0.04	0.01	0.05	0.07	0.07	0.17	0.00
Log (Market Cap)	0.15	1.00	-0.18	0.02	0.33	0.30	0.77	0.75	0.03
Absolute Abnormal Return	-0.04	-0.18	1.00	0.27	0.03	0.11	-0.12	-0.09	0.01
Abnormal Turnover	0.01	0.02	0.27	1.00	0.08	0.17	0.02	0.01	0.00
News Dummy	0.05	0.33	0.03	0.08	1.00	0.40	0.32	0.33	0.02
Chunky News Dummy	0.07	0.30	0.11	0.17	0.40	1.00	0.25	0.38	0.02
Log(1+# of Analysts)	0.07	0.77	-0.12	0.02	0.32	0.25	1.00	0.63	0.05
Log (Chunky News Last Year)	0.17	0.75	-0.09	0.01	0.33	0.38	0.63	1.00	0.06
Advert. Expense / Sales	0.00	0.03	0.01	0.00	0.02	0.02	0.05	0.06	1.00

Table 2: The *Level* of SVI and Alternative Measures of Attention

The dependent variable in each regression is the natural logarithm of weekly aggregate search frequency (SVI). Log(Market Capitalization) is the natural logarithm of market capitalization, Abnormal return is the value of the concurrent week DGTW abnormal return, Absolute Abnormal return is its absolute, Abnormal Turnover is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007), News Dummy is a dummy variable which takes the value 1 if there is a news story in the Dow Jones news archive in the concurrent week, Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive in the concurrent week, Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S, Advertising Expense / Sales is the ratio between the advertising expense and sales in the previous fiscal year and Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last 52 weeks. Robust standard errors clustered by firm are in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% level.

	(1)	(2)	(3)	(4)	(5)
Intercept	-3.071***	-2.960***	-3.401***	-3.420***	-2.996***
	(0.404)	(0.400)	(0.460)	(0.460)	(0.462)
Log(Market Capitalization)	0.189***	0.182***	0.223***	0.224***	0.141***
	(0.028)	(0.028)	(0.038)	(0.038)	(0.042)
Absolute Abnormal Return	-0.142	-0.307	-0.288	-0.300	-0.509
	(0.377)	(0.373)	(0.376)	(0.376)	(0.370)
Abnormal Turnover	0.020***	0.015*	0.017**	0.017**	0.025***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
News Dummy	0.033				
	(0.038)				
Chunky News Dummy		0.103***	0.102***	0.101***	0.010
		(0.030)	(0.030)	(0.030)	(0.014)
Log(1+Number of Analysts)			-0.113*	-0.115*	-0.154**
			(0.065)	(0.065)	(0.066)
Advertising Expense / Sales				0.970	0.656
				(1.314)	(1.311)
Log(Chunky News Last Year)					0.277***
					(0.070)
Week Fixed Effects	YES	YES	YES	YES	YES
Observations	347,997	347,997	335,183	335,183	335,032
Clusters (firms)	2,325	2,325	2,307	2,307	2,307
R^2	0.045	0.045	0.046	0.046	0.052

Table 3: The *Change* in SVI and Alternative Measures of Attention

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

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.030***	-0.024***	-0.022***	-0.022***	-0.025***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Log(Market Capitalization)	0.001***	0.001***	0.001*	0.001*	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Absolute Abnormal Return	0.220***	0.211***	0.211***	0.211***	0.213***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)
Abnormal Turnover	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
News Dummy	0.000				
	(0.001)				
Chunky News Dummy		0.005***	0.005***	0.005***	0.005***
		(0.001)	(0.001)	(0.001)	(0.001)
Log(1+Number of Analysts)			0.001	0.001	0.001
			(0.001)	(0.001)	(0.001)
Advertising Expense / Sales				0.008	0.010
				(0.014)	(0.014)
Log(Chunky News Last Year)					-0.002***
					(0.001)
Week Fixed Effects	YES	YES	YES	YES	YES
Observations	344,260	344,260	331,909	331,909	331,764
Clusters (firms)	2,195	2,195	2,187	2,187	2,187
R^2	0.027	0.028	0.028	0.028	0.028

Table 4: Vector Autoregression (VAR) Model of Attention Measures

We compare four weekly measures of attention using Vector Autoregressions (VAR). Log(SVI) is the natural logarithm of weekly aggregate search frequency (SVI); Log(Turnover) is the natural logarithm of weekly turnover; Absolute Abnormal return is the absolute value of the concurrent week DGTW abnormal return; and Log(1+Chunky News) is the natural logarithm of one plus the number of chunky news stories during the concurrent week. We run the VAR for each stock with at least two years of weekly data. We include both a constant and a time trend in the VAR. The VAR coefficients are then averaged across stocks. *, ** and *** represent significance at the 10%, 5% and 1% level.

	Lagged One Week				
	log(SVI)	log(turnover)	Absolute Abnormal return	log(1+ Chunky News)	R2
log(SVI)	0.4990***	-0.0041***	0.0075	-0.0036***	52.61%
	(0.0056)	(0.0009)	(0.0117)	(0.0006)	
log(turnover)	0.0053	0.4425***	0.5642***	-0.0201***	40.33%
	(0.0056)	(0.0009)	(0.0117)	(0.0006)	
Absolute Abnormal return	0.0030***	0.0016***	0.0356***	-0.0008***	5.65%
	(0.0056)	(0.0009)	(0.0117)	(0.0006)	
log(1+Chunky News)	0.0695***	0.0153***	0.1078**	-0.0099***	4.28%
	(0.0056)	(0.0009)	(0.0117)	(0.0006)	

Table 5: Change in SVI and Individual Trading Reported by Dash-5

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

In both panels, we regress monthly changes (log difference) in the number of individual orders (Δ Order) or monthly changes (log difference) in the individual turnover (Δ Turnover) on several variables. These include monthly SVI change, alternative measures of attention and other stock characteristics. SVI Change is the difference between the logarithm of SVI during month (t) and the logarithm of SVI during month (t-1), aggregated from weekly SVI. Among alternative measures of attention, Log(Market Cap) is the logarithm of the prior month-end (t-1) market capitalization; RET(t) is the monthly return from the current month (t); |RET(t)| is the absolute value of the return of the stock during month (t); Chunky News Dummy takes the value of one if there is at least one chunky news story in the Dow Jones News archive during month (t); Advert. Expense/Sales ratio is the latest advertisement expenditure to sales ratio available from Compustat prior to month (t), where we set advertisement expenditure equal to zero if advertisement expenditure is missing. Among other stock characteristics, B/M is the book to market value of the equity, where the book value of the equity is from the latest available annual accounting statement and the market value of the equity is the month-end close price times the number of shares outstanding at the end of month (t-1); Non-institutional Holding (Q-1) is computed as one minus the percentage of stocks held by all S34-filing institutional shareholders at the end of quarter prior to the current quarter; Return Volatility is the standard deviation of individual stock return estimated from daily returns during quarter (Q-1); Δ [log(Turnover)] is the difference between the natural logarithm of total stock turnover reported by CRSP in month (t-2) and month (t-1); RET(t-1) is the one-month return prior to current month t; RET[t-13, t-2] is the cumulative stock return between months (t-13) and (t-2); RET[t-36, t-14] is the cumulative stock return between months (t-36) and (t-14). Finally, Madoff is a dummy variable taking value of one for all observations from the Madoff Security, and taking value of zero for all observations from the New York Stock Exchange (for NYSE-listed stocks) and Archipelago Holdings (for NASDAQ-listed stocks).

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

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

	Order Size: 100 – 1999 shares		Order Size: 100 – 9999 shares	
	Δ Order	Δ Turnover	Δ Order	Δ Turnover
	(1)	(2)	(3)	(4)
SVI Change (t-1, t)	0.062***	0.070***	0.060***	0.094***
	(0.015)	(0.015)	(0.015)	(0.016)
Log(Market Cap) (t-1)	-0.010***	-0.010***	-0.010***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
RET (t)	0.103***	0.083***	0.108***	0.008
	(0.016)	(0.017)	(0.015)	(0.019)
|RET(t)|	1.080***	1.225***	1.193***	1.731***
	(0.025)	(0.026)	(0.023)	(0.028)
Chunky News Dummy (t)	0.094***	0.099***	0.101***	0.131***
	(0.003)	(0.003)	(0.003)	(0.003)
Advert. Expense / Sales (t)	-0.017	-0.045	-0.022	-0.086**
	(0.028)	(0.030)	(0.027)	(0.039)
B/M (t-1)	-0.008***	-0.008***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Non-Institutional Holding (Q-1)	0.031***	0.030***	0.032***	0.033***
	(0.003)	(0.004)	(0.004)	(0.004)
Return Volatility (Q-1)	-0.049***	-0.055***	-0.055***	-0.075***
	(0.002)	(0.002)	(0.002)	(0.003)
Δ [log(Turnover)] (t-1)	-0.146***	-0.174***	-0.166***	-0.269***
	(0.004)	(0.004)	(0.004)	(0.004)
RET(t-1)	0.137***	0.086***	0.110***	-0.040**
	(0.021)	(0.021)	(0.019)	(0.020)
RET [t-13, t-2]	0.009**	0.008**	0.002	-0.000
	(0.004)	(0.004)	(0.003)	(0.002)
RET [t-36, t-14)	-0.003***	-0.003***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.190***	0.207***	0.184***	0.204***
	(0.018)	(0.019)	(0.018)	(0.022)
Month Fixed Effect	YES	YES	YES	YES
Observations	88,048	88,048	88,048	88,048
Number of Clusters (Stock)	2,444	2,444	2,444	2,444
R^2	0.211	0.219	0.238	0.266

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

	Madoff		NYSE/ARCH		Comparison	
	Δ Order	Δ Turnover	Δ Order	Δ Turnover	Δ Order	Δ Turnover
	(1)	(2)	(3)	(4)	(5)	(6)
SVI Change (t-1, t)	0.181***	0.191***	0.054***	0.083***	0.084***	0.136***
	(0.037)	(0.043)	(0.016)	(0.017)	(0.027)	(0.030)
SVI Change X Madoff					0.102***	0.054**
					(0.027)	(0.027)
Madoff					-0.006***	-0.008***
					(0.001)	(0.001)
Log(Market Cap) (t-1)	-0.005***	-0.010***	-0.011***	-0.014***	0.067**	-0.054*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.028)	(0.032)
RET (t)	0.154***	0.059	0.042**	-0.047**	1.101***	1.635***
	(0.045)	(0.050)	(0.017)	(0.020)	(0.040)	(0.047)
|RET(t)|	1.388***	1.866***	1.131***	1.642***	0.072***	0.104***
	(0.062)	(0.070)	(0.025)	(0.029)	(0.007)	(0.008)
Chunky News Dummy (t)	0.064***	0.097***	0.104***	0.135***	-0.025	-0.058
	(0.010)	(0.013)	(0.003)	(0.004)	(0.055)	(0.059)
Advert. Expense / Sales (t)	-0.061	-0.071	-0.039*	-0.098***	-0.006**	-0.005
	(0.076)	(0.082)	(0.021)	(0.037)	(0.003)	(0.003)
B/M (t)	-0.008*	-0.005	-0.007***	-0.009***	-0.008	-0.004
	(0.005)	(0.005)	(0.002)	(0.002)	(0.010)	(0.012)
Non-Inst. Holding (Q-1)	-0.033**	-0.020	0.037***	0.042***	-0.047***	-0.067***
	(0.015)	(0.018)	(0.004)	(0.005)	(0.003)	(0.003)
Return Volatility (Q-1)	-0.052***	-0.068***	-0.054***	-0.074***	-0.177***	-0.272***
	(0.004)	(0.005)	(0.002)	(0.003)	(0.007)	(0.008)
Δ [log(Turnover)] (t-1)	-0.182***	-0.270***	-0.157***	-0.254***	0.027	-0.181***
	(0.011)	(0.013)	(0.005)	(0.006)	(0.030)	(0.035)
RET(t-1)	-0.050	-0.332***	0.161***	0.043**	0.011**	0.011*
	(0.045)	(0.055)	(0.015)	(0.017)	(0.005)	(0.006)
RET [t-13, t-2]	0.012*	0.008	0.010**	0.010**	-0.000	0.001
	(0.006)	(0.007)	(0.005)	(0.004)	(0.001)	(0.001)
RET [t-36, t-14)	0.001	0.002	-0.002***	-0.002**	0.098***	0.119***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.028)	(0.034)
Constant	0.097**	0.186***	0.187***	0.229***	0.084***	0.136***
	(0.043)	(0.050)	(0.019)	(0.023)	(0.027)	(0.030)
Month Fixed Effect	YES	YES	YES	YES	YES	YES
Observations	28,774	28,774	84,418	84,418	56,876	56,876
Number of Clusters (Stock)	1,043	1,043	2,359	2,359	1,025	1,025
R^2	0.131	0.127	0.299	0.291	0.173	0.191

Table 6: Pre-IPO SVI Change, IPO Characteristics and IPO First-Day Return Regressions

This table regresses IPO first-day return on the pre-IPO week SVI Change and IPO characteristics. The dependent variable is the individual IPO's first-day return, computed as the first CRSP available closing price divided by the offering price minus one. SVI_Change is defined as the log of SVI during the week prior to the IPO week (w-1) minus the log of the median SVI (w-9, w-2), where w is the week the company went public. Offer/Medium Price is the ratio of the offering price divided by the medium of the filing price. Log(Offering Size) is the logarithm of offering size, where the offering size is defined as the offering price multiplied by the number of shares offered. Industry Return is the Fama-French 48-industry portfolio return corresponding to the industry classification of the IPO at the time of public offering. The Sample period of IPOs is from 2004 to 2007. Only regular and common stock IPOs traded on NYSE, AMEX and NASDAQ with valid SVI (searched using company names) are retained in the sample. Only the IPOs with the first available CRSP close price less than or equal to five days are retained. The standard errors (in parentheses) are clustered by the offering year and month. *, ** and *** denote the regression coefficients are statistically significant at the 10%, 5% and 1% level respectively.

	(1)	(2)
SVI_Change	0.257***	0.171**
	(0.089)	(0.070)
Offer/Medium Price		0.349*
		(0.203)
Log(Offering Size)		0.028
		(0.027)
Industry Return [t-7, t-1]		-0.044
		(0.111)
Constant	0.116***	-0.229
	(0.016)	(0.359)
Observations	181	179
R^2	0.043	0.201

Table 7: Pre-IPO SVI, IPO Characteristics and Post-IPO Return Regressions

This table considers the cumulative IPO raw return (Panel A) and cumulative IPO return adjusted by the cumulative industry returns (Panel B) during the fourth to the twelfth month after the initial public offering. The dependent variable in Panel A is the individual IPO's cumulative return during the [4, 12] window after the initial public offering. The dependent variable in Panel B is the individual IPO's return adjusted by the cumulative industry return during the [4, 12] window after the initial public offering. SVI_Change is defined as the log of SVI during the week prior to the IPO week (w-1) minus the log of median SVI (w-9, w-2), where w is the week the company went public. First-day Return is computed as the first CRSP available closing price divided by the offering price minus one. Offer/Medium Price is the ratio of the offering price divided by the medium of the filing price. Log(Offer Size) is the logarithm of the offering size, where the offering size is defined as the offering price multiplied by the number of shares offered. Industry Adjusted IPO Return is the cumulative return of the IPO (adjusted by the industry return) during the first three months after the IPO. Industry Return is the Fama-French 48-industry portfolio return between the seventh month and the first month prior to the IPO, where the industry classification of the IPO corresponds to the industry classification of the IPO at the time of public offering. Turnover Ratio (First Week) is the average daily turnover during the week of the IPO. The Sample period of IPOs is from 2004 to 2007. Only regular and common stock IPOs traded on NYSE, AMEX and NASDAQ with valid SVI (searched using company names) are included. Only the IPOs with first available CRSP close prices less than or equal to five days are retained in the sample. The standard errors (in parentheses) are clustered by the offering year and month. *, ** and *** denote the regression coefficients are statistically significant at the 10%, 5% and 1% level respectively.

	A. Raw IPO Return			B. Industry Adjusted IPO Return		
	(1)	(2)	(3)	(4)	(5)	(6)
SVI_Change	0.163	0.164	-0.299	0.240	0.240	-0.227
	(0.350)	(0.349)	(0.237)	(0.337)	(0.335)	(0.213)
SVI_Change x First-day Return	-2.027**	-2.047**		-2.047**	-2.063**	
	(0.949)	(0.917)		(0.967)	(0.929)	
Offer/Medium Price x First-day Return	-0.106		-0.299	-0.089		-0.284
	(0.567)		(0.577)	(0.552)		(0.554)
First-day Return	0.058	0.038	-0.082	0.099	0.083	-0.042
	(0.211)	(0.165)	(0.208)	(0.200)	(0.152)	(0.208)
Offer/Medium Price	0.185	0.187	0.115	0.196	0.198	0.126
	(0.199)	(0.196)	(0.197)	(0.192)	(0.189)	(0.187)
Log(Offering Size)	0.067*	0.066*	0.064	0.066**	0.066**	0.063*
	(0.038)	(0.037)	(0.040)	(0.032)	(0.031)	(0.035)
Industry Adjusted IPO Return [t+1, t+3]	0.070	0.070	0.087	0.067	0.067	0.085
	(0.183)	(0.182)	(0.176)	(0.186)	(0.185)	(0.180)
Industry Return [t-7, t-1]	0.335	0.332	0.347	0.149	0.147	0.161
	(0.360)	(0.359)	(0.365)	(0.301)	(0.299)	(0.305)
Turnover Ratio (First Week)	-0.284	-0.283	-0.299	-0.413	-0.413	-0.428
	(0.595)	(0.591)	(0.613)	(0.545)	(0.542)	(0.557)
Constant	-0.820*	-0.805*	-0.746	-0.848**	-0.835**	-0.773*
	(0.483)	(0.461)	(0.518)	(0.415)	(0.396)	(0.451)
Observations	172	172	172	172	172	172
R^2	0.063	0.063	0.041	0.064	0.064	0.038

Table 8: Size, Change in SVI (*SVI_Change*), and Russell 3000 Stock Portfolio Returns

Each week, we sort Russell 3000 stocks in our sample based on their market capitalization into three groups. Within the large (top third) and small (bottom third) of Russell stock groups, we further sort stocks based on their SVI_Change in that week into five portfolios. SVI_Change is defined as the log of SVI during the week minus the log of median SVI during the previous eight weeks. Average future portfolio returns up to twenty-six weeks are reported. We report both the raw returns and the DGTW characteristics-adjusted returns which control for size, book-to-market and past return characteristics. The t-values associated with spread portfolio returns are computed using the Newey-West formula, with the lag equal to the number of overlapping months. In Panel A, we use the original SVI_Change. In Panel B, we use the Residual SVI_Change, which is orthogonal to alternative measures of attention. "Noisy" tickers are also excluded in Panel B. The sample period is from January 2004 to June 2008.

Panel A: Portfolios constructed using SVI_Change

Port	N	Return (%)						DGTW-adj Return (%)					
		w 1	w 2	w 3	w 4	w 1-4	w 1-26	w 1	w 2	w 3	w 4	w 1-4	w 1-26
Large Russell Stocks													
High	110	0.18	0.17	0.18	0.20	0.70	4.16	0.05	0.04	0.04	0.07	0.19	0.61
2	110	0.17	0.18	0.18	0.18	0.69	4.22	0.03	0.05	0.05	0.05	0.17	0.62
3	110	0.16	0.17	0.17	0.16	0.64	4.22	0.04	0.05	0.06	0.04	0.19	0.79
4	110	0.16	0.16	0.13	0.14	0.58	4.21	0.04	0.02	0.00	0.03	0.07	0.59
Low	110	0.18	0.20	0.19	0.17	0.73	4.38	0.05	0.06	0.07	0.04	0.21	0.76
H-L		-0.01	-0.03	-0.01	0.03	-0.03	-0.23	0.01	-0.02	-0.03	0.03	-0.02	-0.15
NW-t		-0.16	-0.78	-0.25	0.88	-0.40	-1.18	0.16	-0.57	-0.80	0.99	-0.37	-1.03
Small Russell Stocks													
High	110	0.20	0.22	0.13	0.12	0.65	3.72	0.17	0.17	0.07	0.07	0.47	1.88
2	110	0.17	0.15	0.22	0.18	0.68	4.33	0.12	0.09	0.17	0.11	0.48	2.88
3	110	0.16	0.18	0.15	0.16	0.63	4.03	0.12	0.14	0.10	0.13	0.48	2.78
4	110	0.11	0.13	0.12	0.15	0.51	3.91	0.04	0.05	0.06	0.10	0.27	2.49
Low	110	0.10	0.10	0.13	0.11	0.43	3.57	0.06	0.03	0.06	0.05	0.20	2.14
H-L		0.10	0.12	0.00	0.01	0.22	0.15	0.11	0.14	0.01	0.02	0.27	-0.25
NW-t		1.87	2.34	0.03	0.21	2.10	0.59	2.04	2.52	0.15	0.39	2.62	-0.85

Panel B: Portfolio constructed using Residual SVI_Change, Noisy Tickers Excluded

Port	N	Return (%)						DGTW-adj Return (%)					
		w 1	w 2	w 3	w 4	w 1-4	w 1-26	w 1	w 2	w 3	w 4	w 1-4	w 1-26
Large Russell Stocks													
High	92	0.21	0.23	0.20	0.23	0.84	4.57	0.04	0.04	0.03	0.06	0.15	0.78
2	92	0.19	0.19	0.22	0.21	0.79	4.33	0.01	0.01	0.05	0.04	0.11	0.54
3	92	0.19	0.24	0.19	0.21	0.81	4.41	0.03	0.07	0.04	0.04	0.17	0.72
4	92	0.17	0.20	0.16	0.18	0.70	4.40	0.02	0.01	-0.01	0.01	0.02	0.67
Low	92	0.22	0.23	0.23	0.21	0.87	4.80	0.04	0.04	0.07	0.03	0.18	0.98
H-L		-0.01	0.00	-0.03	0.02	-0.04	-0.23	0.00	0.00	-0.04	0.03	-0.03	-0.20
NW-t		-0.26	0.11	-0.92	0.46	-0.49	-1.14	-0.02	-0.10	-1.08	0.83	-0.35	-1.09
Small Russell Stocks													
High	92	0.28	0.27	0.17	0.18	0.87	3.83	0.19	0.18	0.07	0.08	0.50	1.65
2	92	0.20	0.22	0.28	0.20	0.88	4.57	0.12	0.11	0.18	0.09	0.47	2.49
3	92	0.14	0.23	0.18	0.23	0.76	4.30	0.07	0.12	0.09	0.12	0.39	2.33
4	92	0.13	0.15	0.16	0.19	0.61	4.07	0.04	0.03	0.07	0.09	0.23	2.27
Low	92	0.15	0.14	0.15	0.16	0.60	3.77	0.06	0.04	0.06	0.06	0.21	1.92
H-L		0.12	0.13	0.02	0.02	0.27	0.06	0.13	0.14	0.01	0.02	0.29	-0.27
NW-t		2.22	2.18	0.31	0.30	2.54	0.20	2.32	2.34	0.25	0.40	2.74	-0.91

Table 9: Change in SVI (*SVI_Change*) and Russell 3000 Stock Returns: Regression Results

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

	1st Week	2nd Week	3rd Week	4th Week
Intercept	32.879*	27.293	-6.485	22.948
	(19.745)	(16.956)	(16.337)	(15.601)
Change in SVI	158.095**	128.874*	41.984	-47.896
	(69.667)	(67.497)	(59.438)	(53.067)
Log Market Cap * Change in SVI	-11.260**	-8.691*	-2.886	3.622
	(4.591)	(4.432)	(3.872)	(3.446)
Log Market Cap	1.702*	1.535	2.422**	1.944**
	(1.009)	(1.010)	(1.017)	(0.990)
Percent Dash-5 Volume * Change in SVI	1346.311***	246.420	-200.594	-364.665
	(438.217)	(565.455)	(590.818)	(467.323)
Percent Dash-5 Volume	4.929	10.635	-14.891	-83.825
	(78.806)	(93.671)	(117.082)	(125.077)
Absolute Abnormal Return	28.038	-89.623**	-6.113	-35.749
	(41.754)	(40.115)	(37.051)	(37.384)
Advertising Expense / Sales	-99.940***	-116.994***	-121.554***	-116.808***
	(29.642)	(30.733)	(28.370)	(28.091)
Log(1 + # of analysts)	-6.395***	-6.196***	-6.929***	-6.226***
	(1.527)	(1.516)	(1.526)	(1.518)
Chunky News last year	-3.368**	-3.606**	-3.678**	-3.778**
	(1.642)	(1.645)	(1.631)	(1.595)
This Week Chunky News Dummy	0.740	0.979	-2.247	0.230
	(1.883)	(1.840)	(1.829)	(1.807)
Abnormal Turnover	2.628***	2.725***	1.322	0.392
	(0.825)	(0.789)	(0.805)	(0.835)
Observations	328080	327717	327357	326999
Week Fixed Effects	YES	YES	YES	YES
Clusters (firms)	2169	2166	2165	2179
R-Squared	0.001831	0.001801	0.001776	0.001735

Table 10: Level of SVI and Price Momentum

Each week, we sort Russell 3000 stocks in our sample on the level of their SVI into five groups. Within each group, we then sort the stocks further into five portfolios based on their return during the week. Stocks in the highest return portfolio are the winners, and stocks in the lowest return portfolio are the losers. In Panel A, we report the returns to momentum strategies (winners minus losers) for the highest SVI stock group and the lowest SVI stock group. We report both the raw returns and the DGTW characteristics-adjusted returns which control for size, book-to-market and past return characteristics. The t-values associated with spread portfolio returns are computed using Newey-West formula, with the lag equal to the number of overlapping months. In Panel B, we report the average stock characteristics for the momentum stocks. ThisWeek_Ret_Diff is the winner-minus-loser return during the current week. Log(Market Cap) is the natural logarithm of market capitalization. Turnover is the weekly turnover. Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive. Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last fifty-two weeks. Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S. Absolute Abnormal Return is the absolute value of the concurrent week DGTW abnormal return. Advertising Expense / Sales is the ratio between the advertising expense and sales in the previous fiscal year. Panel C is similar to Panel A except that we first sort on analyst coverage. Panel D is similar to Panel A except that we replace SVI with Residual SVI which is orthogonal to alternative measures of attention and excludes “noisy” tickers. The sample period is from January 2004 to June 2008.

Panel A: Momentum Profits in the High- and Low-SVI stock groups

Port	N	Cumu. Return (%)					Cumu. DGTW-adj Return (%)				
		w 1-4	w 1-8	w 1-13	w 1-26	w 1-52	w 1-4	w 1-8	w 1-13	w 1-26	w 1-52
High	65	0.34	0.65	1.05	2.44	4.63	0.30	0.46	0.77	1.84	3.87
Low	65	-0.14	0.06	0.24	0.95	2.18	-0.28	-0.15	-0.11	0.54	1.45
H-L		0.48	0.59	0.81	1.49	2.45	0.58	0.60	0.88	1.30	2.41
NW-t		2.90	2.31	2.58	2.43	2.73	3.64	2.37	2.61	1.66	2.37

Panel B: Average Portfolio Characteristics

Port	Log (SVI)	ThisWeek _Ret_Diff	Log (Market Cap)	Turn over	Chunky News Dummy	Log(Chunky News Last Year)	Log(1+# of analysts)	Absolute Abnormal Return	Advertising Expense / Sales
High	3.00	0.1099	14.25	0.06	0.41	3.46	1.98	0.0553	0.0350
Low	-2.29	0.1177	13.61	0.06	0.33	3.09	1.81	0.0591	0.0310
H-L	5.30	-0.0078	0.64	0.00	0.08	0.37	0.18	-0.0038	0.0040
NW-t	*111.86*	*-8.63*	*23.95*	*1.75*	*21.80*	*53.90*	*22.14*	*-8.33*	*3.28*

Panel C: Momentum Profits in the High- and Low-Analyst-coverage stock groups

Port	N	Cumu. Return (%)					Cumu. DGTW-adj Return (%)				
		w 1-4	w 1-8	w 1-13	w 1-26	w 1-52	w 1-4	w 1-8	w 1-13	w 1-26	w 1-52
High	83	-0.23	-0.14	0.07	1.22	2.81	-0.24	-0.16	0.08	0.96	1.60
Low	83	-0.67	-0.67	-0.23	0.08	1.41	-0.72	-0.70	-0.40	0.11	1.66
H-L		0.45	0.53	0.30	1.15	1.39	0.48	0.54	0.48	0.86	-0.07
NW-t		1.82	1.50	0.52	1.14	0.89	1.91	1.61	0.82	1.06	-0.07

Panel D: Momentum Profits in the High- and Low-Residual-SVI stock groups, Noisy Tickers excluded

Port	N	Cumu. Return (%)					Cumu. DGTW-adj Return (%)				
		w 1-4	w 1-8	w 1-13	w 1-26	w 1-52	w 1-4	w 1-8	w 1-13	w 1-26	w 1-52
High	55	0.10	0.12	0.54	1.91	3.77	0.14	0.14	0.52	1.94	3.75
Low	55	-0.13	-0.01	0.14	0.65	1.70	-0.21	-0.08	0.06	0.70	1.20
H-L		0.23	0.14	0.40	1.26	2.07	0.35	0.22	0.46	1.24	2.55
NW-t		1.23	0.47	1.30	2.20	2.65	1.91	0.80	1.39	2.03	2.67

Table 11: Level of SVI and Price Momentum: Regression Results

The dependent variables are the DGTW cumulative abnormal returns for different future holding periods. Return is the stock return during the current week; Log(SVI) is the log of SVI during the current week; Log(Chunky News Last Year) is the natural logarithm of the number of Chunky News stories in the last fifty-two weeks; Chunky News Dummy is a dummy variable that takes the value 1 if there is a news story with multiple story codes in the Dow Jones news archive; Log(1+Number of Analysts) is the natural logarithm of the number of analysts in I/B/E/S; Abnormal Turnover is standardized abnormal turnover as in Chordia, Huh and Subrahmanyam (2007); Log(Market Cap) is the natural logarithm of market capitalization; and Absolute Abnormal Return is the absolute value of the concurrent week DGTW abnormal return. Robust standard errors clustered by firm are in parentheses. *, ** and *** represent significance at the 10%, 5% and 1% level. The sample period is from January 2004 to June 2008.

	Week 1-4	Week 1-8	Week 1-13	Week 1-26	Week 1-52
Return	0.128**	0.158**	0.114	0.373**	0.946***
	(0.054)	(0.076)	(0.107)	(0.185)	(0.365)
Return x log(SVI)	0.004	0.003	0.007	0.019**	0.043**
	(0.002)	(0.003)	(0.005)	(0.009)	(0.020)
Return x Log(Chunky News Last Year)	0.031***	0.033***	0.037**	0.031	-0.041
	(0.008)	(0.012)	(0.016)	(0.028)	(0.064)
Return x Chunky News Dummy	0.064***	0.071***	0.074***	0.065**	0.149***
	(0.010)	(0.014)	(0.018)	(0.026)	(0.048)
Return x Log(1+Number of Analysts)	-0.015*	-0.018*	-0.032**	-0.041	-0.125*
	(0.008)	(0.011)	(0.014)	(0.028)	(0.066)
Return x Abnormal Turnover	0.012***	0.016***	0.008	0.012	0.001
	(0.003)	(0.005)	(0.006)	(0.011)	(0.022)
Return x Log (Market Cap)	-0.016***	-0.017**	-0.011	-0.023	-0.036
	(0.005)	(0.007)	(0.010)	(0.018)	(0.038)
Return (t) x Absolute Abnormal Return	-0.333***	-0.342**	-0.376**	-0.295	0.024
	(0.106)	(0.142)	(0.186)	(0.284)	(0.681)
Constant	0.002***	0.004***	0.006***	0.011***	0.022***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.005)
Week Fixed Effect	YES	YES	YES	YES	YES
Observations	333932	332498	325892	300744	251307
Cluster (Firm)	2301	2294	2275	2193	2081
R^2	0.002	0.003	0.003	0.003	0.003