Mediating Investor Attention

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Abstract

We review the literature on investor attention with a focus on studies of events that attract investors' attention. Such events are associated with sharp short-term price reactions, often followed by reversals, an asymmetry in price reactions with stronger responses to positive signals, increases in trading volume, and an asymmetrical effect on the buying and selling of individual investors who tend to be on the buy side of the market for attention-attracting stocks. Most studies we discuss document some, but not all, of these phenomena. We analyze 1983-2000 ISSM/TAQ and 2007-2017 TAQ data to show that, for several previously studied attention-attracting events, individual investors are on the buy side of the market. We argue that the primary determinant of individual investor attention is media coverage and location and we discuss support in the literature for this hypothesis.

When faced with a large number of choices, how people allocate attention may determine their choices as much or more than preferences and beliefs. For example, consider an individual investor choosing a U.S. listed stock to purchase. She faces thousands of alternatives. It is the rare investor indeed who will carefully consider the how the attributes of each of thousands of stocks satisfy her own preferences and beliefs. Odean (1999) and Barber and Odean (2008) propose that most individual investors solve this daunting search problem by choosing from the small subset of stocks to which their attention has been directed. If the stocks to which an investor's attention is directed do not include the investor's best choices or the choices the investor would have made had she considered the full set of options, attention may greatly influence stock purchase decisions.

People tend to allocate more attention to more salient choices, that is, to choices that differ most noticeably on observed attributes. We propose, however, that which stocks individual investors are aware of and which they ignore is determined primarily by media coverage and location, not by salience. Salience influences how an investor's attention is allocated among the choices presented. But media coverage and the location of that coverage determine what those choices are.

For example, an investor may choose to read the *Wall Street Journal*, but the Journal's editors decide which companies are covered in the Journal and whether those companies appear on the front or back pages. For many, if not most, investors, this filtering by information intermediaries matters more than the salience of securities that pass through the filter. Furthermore, information intermediaries may create salience where it did not previously exist.

One illustration of creating salience is the *Wall Street Journal's* "Dartboard" column, published from October 1988 through April 2002. Every month, four investment professionals each recommended one stock pick. These picks were pitted against four stocks chosen by darts thrown at stock tables on the *Wall Street Journal's* walls. < https://www.wsj.com/articles/SB1019080901714448 0> Barber and Loeffler (1993) investigate the performances of stocks covered by the "Dartboard" column from *Wall Street Journal* from October 1988 through October 1990. They find that the stocks recommended by the "Pros" experienced average positive abnormal returns of 4 percent and double their average trading volume on the two days following the publication of the recommendations. The recommended stocks with the highest trading volumes experienced the highest abnormal returns followed by significant reversals from days 2 to 25.

What brought these stocks to investors' attention was not their inherently salient attributes. Of course, the investment professionals may have chosen to recommend stocks with a compelling narrative, but in most cases, nothing newsworthy had happened to recommended stocks since the previous day's issue of the Journal and these stocks were not receiving unusual coverage in other news outlets. Thus many of the recommended stocks probably did not have attributes that would have attracted the attention of an investor who was scanning information about the entire universe of stocks on his own. What brought these stocks to investors' attention was that they were mentioned in the Journal.

Furthermore, relative to other stocks mentioned in the Journal that day, these stocks were salient, but, again, not because of their inherent attributes. They were salient because they were featured in a prominent, popular, narrative-driven column. The Dartboard column included short bios and a sketch of each expert and as well as a description of the expert's rationale for his or her pick. The column was framed as a contest and readers knew they could look forward to reading in six months[1] about how the experts had fared relative to the darts.

On any day, the thousands of companies listed on US exchanges will not get equal media coverage. Different financial media may highlight stocks for different reasons. Some may cover stocks with attributes that investors would, on their own, find salient such as extreme returns. Some may focus on less salient, yet important, fundamental information that investors might otherwise miss. And some may run stories that simply sell newspapers or increase TV viewership. How stories are packaged also matters. Though Jim Cramer does not mince words when describing the five biggest winners of 2017 on CNBC's *Mad Money*, he leaves number 6 unmentioned.[2] And while

[1] Prior to 1990 expert and dart pick returns were reported after one month.
[2] https://www.cnbc.com/2018/01/03/cramer-reviews-the-dows-biggest-winners-and-losers-for-2017.html

an investor searching all stocks on his own might find the 6th biggest winner nearly as salient as the 5th, Cramer's viewers are unlikely to give number 6 any thought.

In this article, we review recent papers on investor attention, focusing primarily, but not exclusively on individual investors. We discuss how these papers do, or do not, support our hypothesis that coverage by the media is the primary determinant of investor attention. Of course, there are other channels through which a stock may attract investors' attention. For example, an investor may drive by a company's factory, shop in company's store, or purchase a company's product. Or a friend, co-worker, or brother-in-law may recommend a stock. However, while local factories and stores may contribute to individual investors' home bias in ownership (e.g., Huberman, 2001; Grinblatt and Keloharju, 2001; Ivkovich and Weisbenner, 2005; Seasholes and Zhu, 2010), these alternative channels are not likely to result in the systematic short-term changes in investor trading documented in the articles discussed below.

The papers we review examine different measures of investor attention. Some document increased trading volume in conjunction with attention grabbing events. Some document short-term price moves or short-term price moves followed by reversals. Others measure attention more directly by analyzing measures Internet search volume. Most studies we discuss document some, but not all, of these effects. We analyze 1983-2000 ISSM/TAQ and 2007-2017 TAQ data to show that, for several types of previously studied attention-attracting events, individual investors are on the buy side of the market.

I. Salience

Attention is a selective process in which an "organism appears to control the choice of stimuli that will be allowed, in turn, to control its behavior." (Kahneman, 1973) Researchers have studied extensively the features of stimuli that attract our attention and circumstances under which some stimuli are or are not favored. Though our capacity for attention varies with arousal and effort, it is limited. (Kahneman, 1973). Stimuli compete for limited resources (Triesman 1960) and that limit can prevent us from attending to all available stimuli or even all stimuli relevant to a task. Attention is directed towards salient stimuli that stand out from the background on dimensions such as movement, color, brightness, or, on a higher cognitive level, unexpectedness. Salient stimuli have proportionately more influence on behavior (Shinoda, Hayhoe, and Shrivastava 2001).

Odean (1998) argues that investors "overweight salient, anecdotal, and extreme information," relative to abstract, statistical, and base-rate information, and that overweighting probabilities associated with salient information—such as recent extreme returns--and underweighting abstract information—such as earnings announcements--leads to systematic market over- and under-reactions.

Bordalo, Gennaioli, and Shleifer (2013) develop a salience based model of lottery selection in which the payoffs of a lottery that differ most noticeably from other the payoffs of other available lotteries are salient by contrast. The probabilities of salient lotteries are overweighted. Bordalo, Gennaioli, and Shliefer 2013, argue that salience theory can explain investor preference for stocks with positive skewness, and for growth stocks as well as the equity premium and countercyclical variation in market returns.

Our contention is that salience affects investor attention but only for the choices presented to investors and that media coverage and location are the main determinants of the choices investors see.

II. Data and Methods

II.A. Identifying individual investor and institutional investor trades

We identify individual and institutional trades using tick-by-tick transaction level data for US stock markets from the Trade and Quotes (TAQ) and Institute for the Study of Security Markets (ISSM) transaction data over the periods 1983–2000 and 2007-2017.

For the 1983-2000 period we rely on algorithms developed by Lee and Ready (1991) to sign trades as buyer or seller initiated. Following Lee and Radhakrishna (2000), we define trades of less than \$5,000 as individual[3] and greater than \$50,000 as institutional; Lee and Radhakrishna (2000) find that in the 1990-91 TORQ database, 39%

[3] All of our results are qualitatively unchanged if we define small trades as less than \$10,000 (1991 dollars).

of individual investor trades are for less than \$5,000 and only 10% of trades less than \$5,000 are institutional, while 35% of institutional trades are for more than \$50,000 and only 2% of trades greater than \$50,000 are from individuals. To account for changes in purchasing power over time, our trade size cut-offs are based on 1991 real dollars and adjusted annually using the Consumer Price Index (CPI). See Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) for details). Our analysis ends in 2000 because the use of computerized trading algorithms to break up institutional trades renders small trade size a less reliable proxy for trades of individual investors after 2000.

For the period 2007-2017, we identify individual investor purchases and sales from resulting from marketable orders using methodology developed and described in Boehmer, Jones, and Zhang (2017).

The 1983-2000 and 2007-2017 methodologies differ in two important respects. First, for the 1983-2000 period we identify trades of individual investors as buyer or seller initiated. From 2007 to 2017, we identify trades of individual investors as purchases or sales. In aggregate, the dollar value of all purchases and all sales of a stock on a day must be equal. However, there is no such adding up constraint for the dollar value of buyer and seller initiated trades; a greater dollar value of executed trades can result from either buyer initiated trades or seller initiated trades. Second, for the 1983-2000 period, we identify large trades that were most likely initiated by institutional investors. We do not attempt to identify institutional trades for the 2007-2017 period. Though Boehmer, Jones, and Zhang (2017) write that they believe their approach picks up a majority of overall retail trading, the complement to these trades would include many retail trades.

II.B. Calculating order imbalances

To measure buy-sell imbalances, we follow Barber and Odean (2008) by forming daily (or weekly) portfolios of stocks based on sorting criteria such at abnormal trading volume or days in event time. For example, to calculate the buy-sell imbalance for small trades, for each stock on each trading day we calculate the stock's abnormal trading volume as the ratio of the stock's trading volume that day to its average trading volume over the previous one year (i.e., 252 trading days). We sort stocks into vigntiles on the basis of that day's abnormal trading volume. Then we sum the number of small buys (*B*) and small sells (*S*) of stocks in each volume partition on day *t* and calculate buy-sell imbalance for purchases and sales executed that day as:

$$BSI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}} \tag{1}$$

where n_{pt} is the number of stocks in partition *p* on day *t*, NB_{it} is the number of purchases of stock *i* on day *t*, and NS_{it} is the number of sales of stock *i* on day *t*. We calculate the time series mean of the daily buy-sell imbalance (BSI_{pt}) for the days that we have trading data for each investor type. Note that our measure of buy-sell imbalance considers only executed trades; limit orders are counted if and when they execute. If there are fewer than ten trades in a partition on a particular day, that day is excluded from the time series average for that partition. We separately calculate daily buy-sell imbalance for large trades (1983-2000) and retail trades (2007-2017). An analogous procedure is followed to calculate weekly buy-sell imbalances based on contemporaneous weekly abnormal volume sorts.

For daily return sorts, each day (*t-1*), we sort all stocks for which returns are reported in the CRSP NYSE/AMEX/NASDAQ daily returns file into vingtiles based on the one day return. We calculate the time series mean of day *t* daily buy-sell imbalance (BSI_{pt}) for the days that we have trading data. An analogous procedure is followed to calculate weekly buy-sell imbalances based on the previous week's returns.

We also sort stocks daily based on abnormal news intensity. To be included in this analysis, a stock must have at least 10 stocks ticker appearances in the daily news feed from the Dow Jones News Service during the formation period of 207 to 21 days prior to the sorting day. Included stocks without news in the current day are assigned to bin 0. Stocks with news on the current day, t=0, are sorted into quartiles based on the abnormal news measure of (the number of news stories in current day) / (average daily number of news stories from day t = -270 through t = -21. We calculate daily (BSI_{pt}) and its time series average.

We calculate buy-sell imbalances for event day partitions of events analyzed in some of the papers discussed below. Each event e is identified by a stock-date pair: stock $k(e)$, and date $t(e)$ (e.g., stock k is recommended in the WSJ's dartboard column on date t). We calculate the small trade buy-sell imbalance for event e on event day t as

$$BSI_{et} = \frac{NB_{k(e)t(e)} - NS_{k(e)t(e)}}{NB_{k(e)t(e)} + NS_{k(e)t(e)}} \tag{2}$$

where $NB_{k(e)t(e)}$ is the number of small buys and $NS_{k(e)t(e)}$ the number of small sells of stock $k(e)$ on event date $t(e)$. We then calculate the average buy-sell imbalance for all events on day t. If there are fewer than ten trades in a stock on event day t, that stock is excluded from the buy-sell imbalance average for that day. We use the same procedure to calculate small trade buy-sell imbalance for event days $t-10$ through $t+10$. We separately calculate event time buy-sell imbalances for large trades (1983-2000) and retail trades (2007-2017).

From 1983-2000, there are 471 million small buys, 455 million small sells, 190 million large buys, and 172 million large sells. The average small buy size is \$3,179, the average small sell, \$3,106, the average large buy, \$227,786, and average large sell, \$229,749. From 2007-2017, there are 1.60 billion retail buys and 1.52 billion retail sells. The average retail buy size is for \$15,203 and the average retail sell for \$15,626.[4] Each trading day (1983-2000), we calculate the number of small purchases, small sales, and the buy-sell imbalance (i.e., equation 2) for small trades that day. We do the same for large trades from (1983-2000) and for retail trades (2007-2017). Table 1 provides means, medians and other descriptive statistics for these calculations. The time series average buy-sell imbalance for small trades is 2.89% and for retail trades 2.35%. Large trades lean more heavily towards buying with a time series average buy-sell imbalance of 5.12%.

III. The asymmetrical effect of attention on buying and selling

Barber and Odean (2008) propose that attention increases the buying and selling

[4] The average trade size calculations for small, large, and retail trades are not adjusted for inflation.

of individual investors asymmetrically and that attention driven buying by individuals creates price pressure that temporarily increases prices and is followed by lower subsequent returns.

When buying stocks, investors face a huge search problem. There are thousands from which to choose. Investors who do not systematically search for stocks are likely to make purchases from the subset of stocks that catch their attention. Even news that most investors consider negative will result in more purchase volume if a large number of investors hear the news and some take a contrary view.

Selling is different. Individual investors usually own only a few individual stocks and most do not sell short (Barber and Odean, 2000). While negative news could prompt an investor to sell, only the small subset of individual investors who already own the stock are likely to sell; furthermore, these investors probably think about, and consider selling, stocks they already own even on days when those stock aren't in the media.

Thus news or other media attention—both good and bad—create a short-term imbalance in the buying and selling of individual investors that tends to favor buying.

Attention also matters for institutional investors, but less so than for individuals. Institutions have more attention. They are more likely to work in teams, work long hours, and to use computers when searching for stocks to buy or to sell. Institutions typically own more securities than individuals and many institutions do short sell. Thus attention does not affect the buying and selling of institutions in the same asymmetrical way that it affects individual investors.

Barber and Odean (2008) test the hypothesis that individual investors are net buyers of stocks on days when their attention is drawn to a stock using three proxies for investor attention and three databases of individual investor trading records. Their proxies for attention are: high abnormal daily trading volume— if an unusual number of investors trade a stock, it is nearly tautological that an unusual number are paying attention to that stock; extreme positive or negative price moves the previous day; and whether a stock is mentioned in the Dow Jones News Service that day. Their individual investor databases are: 78,000 investors at a large discount brokerage (Jan 1991- Dec 1996) (the LDB dataset), 14,667 investors at a small discount brokerage (Jan 1996 – Jun 1999), and 665,533 investors at a large retail brokerage (Jan 1997 – Jun 1999). They find that for individual investors the average buy-sell imbalance (as defined in Equation 1) is greater on high attention days.[5] An analysis of a smaller set of professional money managers does not yield similar patterns.

We extend this analysis by calculating daily buy-sell imbalances associated with abnormal daily volume, prior day returns, and abnormal daily news coverage for small and for large trades for the 1983-2000 ISSM/TAQ data and retail trades for the 2007-2017 TAQ data. We also calculate weekly buy-sell imbalances for stocks sorted on the same week's abnormal volume, the previous week's return, and same week's abnormal news coverage.

Figure 1 graphs buy-sell imbalances for vingtiles sorted on abnormal daily and weekly abnormal trading volume. Consistent with Barber and Odean's (2008) theoretical model and brokerage data results, small trade and the retail trade imbalances are increasing monotonically and, significantly, in the abnormal volume sorts. Individual investors place progressively more buy orders relative to sells when abnormal trading is higher. Note that they are not simply trading more; they are buying more. The increases are remarkable smooth. The range of the imbalances is tighter for the retail trades, possibly because these include larger retail trades or because of changes in the trading of retail investors over time. The pattern for large trades suggests that the trading of institutional investors is less affected by attention and institutions buy stocks with the highest and lowest abnormal trading volume less aggressively. Sorting stocks on weekly, rather than daily, abnormal volume yields very similar results.

Figure 2 graphs daily (and weekly) buy-sell imbalances for vingtiles sorted on the previous days (or previous week's) return. The results are again consistent with Barber and Odean's (2008) theoretical prediction and brokerage data results. Individual investor buy-sell imbalances are U shaped when sorted on previous period return; that is, individual investors make proportionately more purchases than sales of stocks with extreme recent returns, whether these returns are positive or negative. In contrast, institutions make proportionately fewer purchases of stocks with extreme recent returns. The buying activity of individual investors, but not institutions, appears to be driven by

[5] Barber and Odean (2011) report empirical evidence that stocks tend to underperform the month following high attention days.

attention. As in Figure 1, retail trades for the period 2007-2017 display a similar pattern to small trades for 1983-2000, however the range of imbalances is tighter.

The abnormal trading volume results and the previous period return results confirm that attention leads individual investors to be disproportionately on the buy side of the market. However, abnormal trading volume is a measure of investor attention but does not tell us why investors are paying attention. And investors may pay attention to stocks with extreme recent price moves because these stocks are mentioned in the media or because such moves are salient. In Figure 3 we look at the influence of news on investors' attention and buy-sell imbalances.

Figure 3 graphs daily and weekly buy-sell small and large trade imbalances for abnormal news sorts. On both a daily and weekly basis, the trades of individuals are least likely to be purchases for stocks not mentioned in the news and most likely to be purchases for stocks with high abnormal news coverage. In contrast, institutional trades are least likely to be purchases when abnormal news is high. Individuals, but not institutions, appear to be buying stocks to which their attention is directed by the media.

III.A. Location

One striking example of the importance of where and how an event is reported in the media is Huberman and Regev's (2001) study of EntreMed. On Sunday, May 3, 1998, the New York Times ran a front-page article about a breakthrough in cancer research and mentioned Entre Med (ENMD) a company with licensing rights to the breakthrough. The share price of the stock soared from the previous Friday's close of 12 to 85 Monday morning and closed Monday at 52. However, the development of the potential cancer cure had been reported in an article in Nature five months ago on November 27, 1997. Furthermore, the Nature article had at that time been covered in the New York Times as well as CNN and CNBC and was the subject of an Entre Med news release. The price of ENMD moved from a closing price of 11.75 on November 26th to a closing price of 15.25 on November 28th. Thus the market reaction to a prominently placed story with no new information was much greater than the earlier reaction to the actual new news. Location dominated content. But not similarly for all investors.

In Figure 4, we graph the cumulative number of small purchases minus small sales of EntreMed from October 1997 through December 1998 (the same period graphed in Figure 1 of Huberman and Regev (2001)). We do the same for large trades. Individuals increase buying somewhat in the week following the publication of the Nature article on November 26, 1997. On November 26, there were 15 more buyer initiated small trades than seller initiated small trades; and over the next two weeks 261 more buyer initiated small trades than seller initiated small trades. On November 26 there were 0 more buyer initiated large trades than seller initiated large trades and over the next two weeks 1 more buyer initiated large trades than seller initiated large trades. However the reaction of individuals to the Nature article was tiny compared to the huge spike small trade net buys on May 4th, the day after the New York Times article appeared. On May 4th, there were 2,898 more buyer initiated small trades than seller initiated small trades; and over the next two weeks an additional 1,729 more buyer initiated small trades than seller initiated small trades. In contrast, on May 4th there were only 62 more buyer initiated large trades than seller initiated large trades and over the next two weeks 150 fewer buyer initiated large trades than seller initiated large trades. The New York Times published; individuals bought.

While Huberman and Regev (2001) demonstrate the importance of where and how and event is reported in the media, Engelberg and Parsons' (2011) study of local newspaper coverage of earnings reports focuses on geographic cross-sectional differences in news coverage of the same event. To separate the effect of media coverage from investor's reaction to the underlying event, Engelberg and Parsons (2011) identify 19 local newspapers serving major U.S. cities and examine the trading of individual investors living in or near those cities. The study analyzes trading in the LDB dataset around S&P 500 Index firm earnings announcements.

The authors first determine whether each local newspaper reported an earnings announcement within two days of the announcement. They then analyze whether local news coverage explains differences in local investor trading in earnings announcement firms. After controlling for a host of explanatory variables—including firm-city, firm-earnings date, and city-earnings date fixed effects, they find that local newspaper coverage of a firm's earnings announcement increases local trading in the firm's stock even for non-local stocks. There is, of course, some possibility that local newspapers simply report earnings announcements that of more interest to their readership. To control for this possibility, Engelberg and Parsons (2011) run a second analysis of local investor trading in response to earnings announcements on days on which a local newspaper's delivery was impeded by hail or blizzards. While neither hail nor blizzards significantly suppress local trading in general, they sever the relationship between local newspaper coverage of an earnings announcement and local investor trading. If the local newspaper covers the announcement but the newspapers are not delivered, the effect on local individual investor trading is similar to what happens when the local paper does not report an earnings announcement.

Peress (2014) reports that national newspaper strikes lead to lower trading volume, volatility, and the dispersion of stock returns. He finds that small-cap stocks are most affected by strikes. Peress (2014) also documents a local drop in individual investor trading (LDB data) on days of and in regions of local newspaper strikes in the US..

Fedyk (2018) demonstrates the importance of news location for institutional investors in a context in which the limits of institutional investors' attention are taxed. Bloomberg's editors classify news articles as "primary important" (PI) "secondary important" (SI) or "all other." Primary important articles get "pinned" to the top of Bloomberg terminal screens. Below this, SI and other articles scroll down the screen as they are replaced by new articles. At most three articles are pinned to the top of the screen. Articles remain there until they are either replaced by a new PI article or "a predefined amount of time (on the order of hours) elapses." If a PI article hits its time limit without being replaced by another PI article, the next SI article to be published is pinned to the top of the terminal screen. SI articles are selected to be pinned solely because they were in the right place at the right time; they are not selected based on importance relative to other SI articles.

Fedyk (2018) measures the market reactions to 1,274 SI articles that are pinned to the top of the screen and 8,233 SI articles that are not pinned (from March 2014 to December 2015). In the ten minutes following publication, stocks mention in pinned SI articles experience 280% higher trading volume and 180% large price changes than stocks mentioned in unpinned SI articles. Stocks in pinned articles have strong return drift for the next 30 to 45 minutes but no subsequent drift. Stocks in unpinned articles experience much smaller initial market reactions and drift that continues for 10 to 15 days at which point the average returns to positive and negative pinned and unpinned news are virtually identical.

Not only are pinned SI articles prominently located, but, on average, they remain on the screen much longer than unpinned articles. It is possible that some investors who look at the Bloomberg screen and see both a pinned SI article and unpinned SI article are attracted by the salience of the pinned article. However, it is almost certain, that more investors see the pinned SI articles than the unpinned SI articles. Even for institutional investors, the location of media coverage matters.

III.B. Media Recommendations

Griffin and Tversky (1992) write that "people focus on the strength or extremeness of the available evidence (e.g., the warmth of a letter or the size of an effect) with insufficient regard for its weight or credence (e.g., the credibility of the writer or the size of a sample)." Expert stock recommendations reported in the media are a case in point. These recommendations rarely convey new information nor accurately predict long run performance. But they do garner attention.

As discussed above, Barber and Loeffler (1993) find that stocks recommended from 1988 to 2000 by experts in the *Wall Street Journal's* "dartboard column" experienced positive abnormal returns of 4 percent during the two days of trading beginning the publication date of the column; "in contrast, the Dartboard Stocks experience no significant abnormal returns over the same period." The abnormal returns are followed by partial reversals over the next 25 trading days. Wright (1994) reports a similar finding for the first 20 publications of the dartboard column with a 4.59 percent abnormal return in the two-day publication window and a complete reversal after 36 trading days. Metcalf and Malkiel (1994) examine the dartboard column expert recommendations for 1990 through 1992. They find a one-day announcement effect of 3%, which they attribute to publicity, but no significant evidence of long-term outperformance by the experts. Liang (1999) examines the performance of dartboard expert recommendations and dart picks for 1990 through November 1994. For expert recommendations, he documents a 3.5% abnormal return during the 2-day announcement period; "for the dartboard stocks there is no such price reaction following the announcement." Liang estimates that during the 6-month contest and after adjusting for risk, investors following the experts' recommendations lose 3.8%. Both Barber and Loeffler (1993) and Liang (1999) report a sharp increase in trading volume during the announcement window for the expert recommended stocks but not for the dart picks.

In Figure 5, we graph the buy-sell imbalance of individuals and institutions prior to following the announcement of expert dart board column recommendations and dart picks. There is a sharp increase in the buy-sell imbalance of individuals the day of expert recommendations, decaying over the next week, but no such increase in response to dart picks. Institutional buy-sell imbalance does not react to either the darts or the experts. Thus individual investors appear to be buying stocks recommended in the press although these recommendations do not reveal novel news nor lead to positive abnormal long run returns. Investors do not, however, buy the stocks chosen buy darts even though dart picks are reported in the same column; buying a stock picked by a dart is difficult to reconcile with a self-image as a serious investor.

Several studies look into the recommendations given on the *Wall $treet Week*, an investment TV show originally hosted by Louis Rukeyser aired each Friday evening on PBS in the United States from 1970 to 2002. Recommendations, both positive and negative, were made by regular panelists and by weekly guests, typically successful analysts or money managers.

Pari (1987) documents that the stocks recommended on *Wall $treet Week* during 1983-1984 experienced positive abnormal returns the week after being recommended, but underperformed the market by an average of 1% within two weeks.

Beltz and Jennings (1997) analyze how 800 recommendations made on *Wall $treet Week* during 1990-1992 influence returns and the volume of buyer initiated trades by all market participants.[6] Positive recommendations have positive abnormal returns the week following the broadcast, with strong positive recommendations averaging a cumulative abnormal return (CAR) of 3.93%. These positive returns are followed by reversals with an average CAR of 0% (-1.18%) three (six) months after the broadcast.

[6] Beltz and Jennings (1997) estimate buyer initiated trading volume from the Institute for the Study of Securities Markets (ISSM) quote and trade data.

Positive abnormal buying volume is also observed the week following the broadcast. Negative recommendations have -0.62% abnormal return the trading after the recommendation and a CAR of -3.25% after six months. No abnormal selling volume is observed.

Ferreira and Smith (2003) analyze over 350 recommendations on *Wall $treet Week* for the period 27 December 27, 1996 through December 26, 1997) by matching companies in the sample with control groups of companies with similar size, book-to-market, and industry characteristics. They document an abnormal return of 0.651% the trading day after the broadcast followed by a reversal. However, they estimate that on average recommended stocks outperform stocks with similar characteristics over the two years following the recommendations.

Mad Money with Jim Cramer is a stock market oriented television program broadcast on CNBC Monday through Friday evenings since 2005. Engelberg, Sasseville and Williams (2012) examine the market reaction to 826 first-time buy recommendations on *Mad Money* from July 28, 2005 to February 6, 2009. They construct portfolios of recommended stocks 2 hours before the show airs at 6PM (EST) to capture the price change that follows the recommendation. These portfolios experience an average overnight return of 2.4% followed by a return reversal. This return reversal effect is strongest for 1) stocks otherwise not in the news (i.e., not appearing in a non-Cramer related article in Factiva during a three-day window surrounding the recommendation date); 2) small illiquid stocks with high idiosyncratic volatility and high *Specialness* (i.e, stocks that are difficult to arbitrage); and 3) stocks recommended on evenings when the show's Nielsen Ratings are higher. The correlation between Nielsen Ratings and the overnight return of recommended stocks is strongest when viewership is greater in high-income area. The authors also examine the market reaction to Cramer's negative recommendations. Consistent with the hypothesis that the buying and selling of individual investors respond asymmetrically to attention, stocks with negative recommendations experience a small negative overnight average return of -0.29% without a subsequent reversal.

Neumann and Kenny (2007) examine short-term market responses to 106 buy recommendations and 46 sell recommendations made on *Mad Money with Jim Cramer* between July 26, 2005 and September 16, 2005. They find an average abnormal return of 1.06% from the close of trading the day of a buy recommendation ($t = 0$) to the close on the following trading day ($t = 1$) with most of this return between the close on day t and the open on day 1. They also find statistically weak evidence of a subsequent reversal. Sell recommendations are followed by negative one day return of -0.20% and no reversal.

Lim and Rosario (2010) analyze 10,589 recommendations made on *Mad Money with Jim Cramer* between June 28, 2005 and December 22, 2006. The sort recommendations as buy or sell, by the market cap of the recommended firm, and as "caller" or "non-caller" recommendations. Caller recommendations are those made by Cramer in response to viewer phone calls. Lim and Rosario (2010) find that both buy and sell recommendations have positive cumulative excess returns in the month leading up to the recommendation. The one-day positive market reaction to buy recommendations and negative reaction to sell recommendations is strongest for small capitalization stocks. In contrast to Engelberg, Sasseville and Williams (2012) and Neumann and Kenny (2007), Lim and Rosario (2010) find weak evidence that Cramer's non-caller recommendations, particularly for smalls stocks, are positively correlated with returns over the next six months.

Karniouchina, Moore, and Cooney (2009) analyze 7,160 buy recommendations between made on *Mad Money with Jim Cramer* November 1, 2005 and July 31, 2007. Their study focuses on attributes of these recommendations known to influence the efficacy of paid advertisements, including primacy-recency effects, clutter and competition, and message length. Like other studies, they document positive pre-recommendation returns, strong one-day post recommendation returns, and subsequent reversals. They find greater one-day market reactions to stocks recommended at the beginning (and to a lesser extent at the end) of a program segment and to stocks receiving more detailed recommendations. They do not find that stocks react more strongly when a program has fewer total recommendations.

Keasler and McNeil (2010) study 7,807 recommendations made on *Mad Money with Jim Cramer* between December 1, 2005 through December 31, 2006. They document a strong increase in trading volume following non-caller recommendations; the increase trading volume is particularly pronounced for small capitalization stocks. One day market reactions to non-caller buy recommendations are positive especially so for small capitalization stocks and are followed by reversals over the next 25 trading days. One day market reactions to non-caller sell recommendations are less pronounced than to non-caller buy recommendations; they are negative for mid and small capitalization stocks but virtually 0 for large stocks; reversals are also less pronounced for non-caller sell recommendations than buy recommendations. Keasler and McNeil (2010) conclude that the initial market reactions to recommendations and subsequent reversals are consistent with the price pressure hypothesis.

III.C. Advertising

Though most advertising promotes sales of specific products, advertising can also direct the attention of an investor to a company. More attention increases the likelihood that more investors will buy a stock (while affecting selling less). Grullon, Kanatas and Weston (2004) document that the magnitude of a firm's annual advertising expenditures correlates with greater breath of stock ownership as well as greater trading liquidity. Analyzing consumer survey data from the Landor Image Power, Frieder and Subrahmanyam (2005) find that the proportion of a firm's shareholders who are individual investors is greater for firms with high brand familiarity and high regard for brand quality.

Lou (2014) analyzes the effect of changes in a firm's annual advertising expenditures on the firm's stock performance and on the buy-sell imbalance of individual investors. He finds that firms in the top decile of year-to-year changes in advertising spending outperform those in the bottom decile by 12.58 percent in the ranking year and underperform by 6.96 percent and 9.84 percent in the following two years respectively. Lou calculates monthly small trade buy-sell imbalances for the 1983-2000 ISSM/TAQ data signing trades with the Lee Ready algorithm. He finds that retail investors place proportionately more buy orders for firms that increase their advertising. Lou also presents evidence that managers are aware of exploiting the link between changes in advertising and stock returns. He finds that a firm's advertising tends to increase in anticipation of insider sales, seasoned equity offerings, and stock-financed acquisitions.

Focke, Ruenzi, and Ungeheuer (2014) focus on firms' intraday advertising expenditures for TV, daily expenditures for newspaper and magazines, and monthly Internet, radio, and billboard expenditures compiled by Kantar Media from 1995 through 2012. They measure investor attention using the number of views of a company's Wikipedia page. They find a strong positive correlation between a firm's abnormal advertising spending and both contemporaneous and subsequent Wiki page views. However, they do not find short-term stock price reactions to abnormal advertising.

While most advertising is designed to directly influence consumers, Focke, Niessen-Ruenzi, and Ruenzi (2016) document a second channel by which advertising may influence investor behavior. Firms that spend more on advertising in newspapers receive more positive coverage and less negative coverage by those same newspapers. Thus, not only is advertising likely to direct investors' attention, but it may also lead to biased reporting that sways investors' beliefs.

Fehle, Tsyplakov and Zdorovtsov (2005) look stock trading volume and returns for firms that run commercials during 19 Super Bowls. The classify firms as recognizable or unrecognizable based on whether the firm running the commercial could be identified by watching the commercial. They find that recognizable firms, but not unrecognizable firms, experience positive abnormal returns in a three-day window following the Super Bowl. For the period 1997-2001, they use small trades in the TAQ data signed by the Lee Ready algorithm to identify individual investor trades, they find that for recognizable firms, but not unrecognizable firms, the buy-sell imbalance of individual investors increases in the three days following the Super Bowl.

Mayer (2016) examines returns and trading in the stock of firms sponsoring NCAA football bowl. He finds a significant positive abnormal return the trading day (and week) following the game. Volume increases as does the buy-sell imbalance of individual investors (estimated using signed small trades in the TAQ data from 1993-2014). The magnitude of market reaction and volume are positively correlated with the number of households watching the football game. Mayer also finds a significant increase in Google search volume (SVI) for game sponsors in the week following the game.

III.D. Extraordinary events

Seasholes and Wu (2007) analyze individual investor account level trading on the Shanghai Stock Exchange, the day of and the day after stocks hit a daily upper price limit. They find that, on average, individual investors' buy-sell imbalance (i.e., the value of individual investor purchases minus sales divided by the value of individual investor purchases plus sales), is significantly negative the day upper price limits are hit and significantly positive the following day. Both effects are stronger when fewer upper price limit events occurred on the same day. Seasholes and Wu (2007) also find that more investors buy a stock for the first time the day after an upper price limit was reached than on other days.

Peng and Xiong (2006) develop a theoretical model in which limited attention causes investors to focus more on information about categories such as the market as a whole or an industry than on firm specific information. Li and Yu (2005) look at investor behavior in response to high levels of the Dow Jones Industrial Average Index—a prominent market statistic. They find that the ratio of the current Dow index to the Dow 52-week high (nearness to 52-week high) positively predicts market returns[7] while the ratio of the current Dow index to the historical high (nearness to historical high) negatively predicts market returns.

Yuan (2015) examines the response of individual investors to historical highs of the Dow Jones Industrial Average Index and to front-page news about the market in the New York Times and the Los Angeles Times. Analyzing the ISSM/TAQ data from 1983-1999, Yuan finds that for signed small trades (i.e., less than $10,000) seller initiated orders increase relative to buyer-initiated orders in response to these events. The imbalance shifts in the opposite direction for large trades (i.e., greater than $50,000). Yuan also finds that individual investors in the LDB dataset are more likely to sell stocks when the Dow hits a record high. Furthermore, he sorts stocks on daily abnormal volume (as in Barber and Odean 2008) and finds that the difference in the buy-sell imbalance for high and low abnormal volume stocks is greater for days on which the Dow hits a record high or there is front page market news. Finally, Yuan finds that aggregate mutual fund

[7] George and Hwang (2004) find a similar effect for individual stocks.

flows (1998-2005) respond negatively to highs in the Dow and to front-page market news.

Kaniel and Parham (2016) find that quarterly mutual fund flows into funds mentioned in the *Wall Street Journal* "Category Kings" top 10 ranking lists are substantially higher than flows into funds that just miss making the list. The last fund mentioned in the list experiences nearly a 1/3rd average increase in flows relative to the next highest ranked fund. Thus media coverage versus non-coverage affects investor behavior far more than meaningful differences in fund characteristics. Kaniel and Parham (2016) also show that there is no such increase in flows for funds making similar lists published less prominently and with less catchy titles in the WSJ. This is consistent with the hypothesis that the media influence on investor attention depends on coverage and location as well as salience added by the media.

III.E. Online search as a measure of attention

We contend that the stocks to which investors pay attention is determined primarily by media coverage and location. Investors choose which newspaper they read, TV program they watch, or website they visit, but their attention is then directed to one stock or another by the producers of that content. However, some investors undoubtedly get their trading ideas from sources other than the media and many investors whose choices are inspired by media will seek more information before trading.

Da, Engelberg, and Gao (2011) introduce Internet search queries as a measure of investor attention. Using Google's weekly Search Volume Index (SVI) they define a stock's abnormal Search Volume Index (ASVI) as the log of SVI for a stock's ticker during the week minus the log of the median SVI for that ticker during the previous eight weeks. Consistent with Barber and Odean's (2008) price pressure hypothesis, Da, Engelberg, and Gao (2001) find that increases in ASVI predict higher stock prices in the next two weeks followed by reversals in the next year and that these predictions are strongest for stocks traded more by individual investors. ASVI also positively correlates with first-day IPO returns and long-run IPO underperformance.

We examine the relationship between Da, Engelberg, and Gao's (2011) ASVI measure and retail investor buy-sell imbalance using 2007-2017 TAQ data. We sort stocks on into vingtiles based on weekly ASVI and calculate average retail buy-sell imbalance in the same week for stocks in each vingtile. Average buy-sell imbalances with 95% confidence intervals are graphed in Figure 7 where retail buy-sell imbalance increases nearly monotonically in ASVI. Once again, individual investors are on the buy-side of the market for stocks that catch their attention.

Joseph, Wintoki, and Zhang (2011) also look at the relationships between Google search volume, trading volume, and returns. Their measure of search intensity is Google's weekly normalized and scaled search volume intensity for an S&P 500 stock's ticker. They find that higher search volume in a week predicts higher abnormal trading volume and abnormal returns the following week and that the sensitivity of returns to search volume is greater for stocks that are more difficult to arbitrage.

IV. Inattention

We review the literature that studies events for which the attention of investors—primarily individuals—is attracted to a stock. There is a separate literature on investor inattention. While attracted attention often results in short-term overreactions followed by reversals, inattention leads to underreactions and continued drift.

Influential papers in the investor inattention literature include Hirshleifer and Teoh (2003), Hirsheilfer, Lim, and Teoh (2011), Della Vigna and Pollet (2009), and Hirshleifer, Lim, and Teoh (2009). Hirshleifer and Teoh (2003) and Hirsheilfer, Lim, and Teoh (2011) develop models in which limited investor attention leads to initial under-reaction to earnings announcements and other accounting data followed by drift. Della Vigna and Pollet (2009) show that the initial stock reaction to earnings announcements is smaller and post-earnings announcement drift greater for firms that announce earning on Fridays—when inattention is more likely—than on other weekdays. Hirshleifer, Lim, and Teoh (2009) document that the initial reactions are smaller and post-earnings announcement drift greater for firms announcing earnings on days when many other firms make earnings announcements.

While inattention is often driven by too much competition for investors' attention, it can also result from a lack of insight. Cohen and Frazzini (2008) document that when firms have strong customer-supplier economic links, the stock of one firm will underreact to negative economic news about the other firm. DellaVigna and Pollet (2007) show that stock prices underreact to demographically predictable changes in future demand for products targeted to specific age groups if those changes are 5 to 10 years in the future. Both of these papers analyze examples for which relevant information was available to investors, but investors appear to have not fully appreciated its importance. By highlighting the potential profits from paying closer attention this information, these papers may lead to a reduction in the inattention that they document.

V. The Media is Changing

When Loius Rukeyser first hosted *Wall $treet Week* November 20, 1970,[8] the Public Broadcasting System had been broadcasting for only six weeks. National television was dominated by three networks. Basic cable networks did not yet exist. Investors who wanted to learn about stocks had few choices. They watched Rukeyser on Friday nights. They read the business section of their local newspaper.

By the early 1980s, 4 million US households were watching *Wall $treet Week*,[9] double the circulation of the *Wall Street Journal*.[10] As shown in Engelberg, Sasseville and Williams (2012), Engelberg and Parsons (2001), and Peress (2014), the influence of a TV show or newspaper on market prices depends on how many people watch or read it. Rukeyser and his guests influenced stock prices because a substantial proportion of active investors were watching.

Today investors have thousands of sources of information about stocks: 24-hour cable financial news, online newspapers, searchable commercial websites devoted to the market, SEC websites, blogs, market oriented social media. Investors can choose what type of information they see. If investors are fragmented in the media sources to which they attend, the influence of any one source on aggregate investor behavior is likely to diminish.

Wall $treet Week broadcast on Friday nights. The stock market opened Monday. Investors had time to mull over their decisions and, perhaps, do research. Today most

[8] https://www.nytimes.com/2006/05/03/business/media/03rukeyser.html
[9] https://www.nytimes.com/1990/11/11/business/enduring-not-always-endearing-wall-street-week.html
[10] In 1982 the *Wall Street Journal* had a national circulation of 1,927,963 ('82, Ayer Directory of Publications, 1982, IMS Press)

sources of market information are available while markets are open. Investors can react immediately and may feel an urgency to do so. Thus the market reaction to the media's influence on investor attention is likely to be faster than in the past. Moreover, investors in a hurry to trade may not take the time to verify what they just read and may become increasingly vulnerable to rumors or mistaken information.

VI. Conclusion

We propose that the stocks to which individual investors allocate their attention are determined primarily by media coverage and location. We review dozens of papers on investor attention with an eye to examining our hypothesis and find strong support.

Stocks with no media coverage get little attention. For example in Figure 4, stocks with no news coverage have lower average buy-sell imbalances than stocks with coverage. And Engelberg and Parsons (2001) find that local trading of S&P 500 stocks on earnings announcement days is lower when the local newspaper is on strike or unable to be delivered due to weather conditions. And mutual funds that just miss top ten lists garner fewer inflows than funds that just make the list (Kaniel and Parham (2016)).

Stocks covered in more prominent locations get more attention. Individuals paid little attention to a *Nature* article on EntreMed but a lot of attention to a *New York Times* article published five months later with same information. Not only did trading volume and price spike in response to the *New York Times* article (Huberman and Regev (2001), but, as illustrated in Figure 1, individuals were dramatically on the buy side of the market while institutions were not.

Individual investors tend to be net buyers of stocks that get their attention whether for good or bad reasons. For example, as we see in Figure 2 and in Barber and Odean (2008), individual investor buy-sell imbalances increase for stocks with both extreme positive and extreme negative returns in the previous day or week (while institutional buy-sell imbalances decrease with extreme returns).

Salience plays a role in investor decisions but often only after media coverage and location pare down the choice set. Sometimes salience is determined by stock attributes such as earnings surprises or extreme recent price moves. However, salience is often created by the media itself such as when the *Wall Street Journal*'s dartboard column experts tell engaging stories about the firms they recommend or Jim Cramer throws a yellow penalty flag. In Figure 5 we graph the mean buy-sell imbalance for small and large trades over a 21 event-day window centered on the publication date of the dartboard column and find that individuals actively trade and are on the buy side of the market for stocks recommended by experts in the column but not for stocks picked by the darts. Institutional investors may also be reading the dartboard column, but ignore both the experts and the darts when they trade.

While it is may not be surprising that individuals trade in response to expert recommendations (even recommendations institutions ignore), individuals also trade in response to media coverage with little informational content. The individual investor buy-sell imbalance for the stocks of firms running Super Bowl commercial increases for three days after the Super Bowl, but only if the firms is easily recognized from the commercial (Fehle, Tsyplakov and Zdorovtsov (2005)).

When individual investors pay attention to a stock, they trade it more and tend to be buyers. If many individuals buy a stock in response to an attention-grabbing event, there is a short-term price increase often followed by a reversal, especially so for small stocks that are difficult to arbitrage. Examples include EntreMed (Huberman and Regev 2001), the WSJ's Dartboard Column (Barber and Loeffler (1993), Metcalf and Malkiel (1994), Wright (1994) and Liang (1999)), *Wall $treet Week* (Pari (1987), Beltz and Jennings (1997) and Ferreira and Smith (2003)), and *Mad Money with Jim Cramer*, (Karniouchina, Moore, and Cooney (2009), Kessler and McNeil (2010), Lim and Rosario (2010), Engelberg, Sasseville and Williams (2012)).

Individual investors can buy any of thousands of stock, but most only buy and own a few. Searching those thousands for one's preferred choices is a daunting task. Barber and Odean (2008) propose that most investors solve this search problem by choosing from the much smaller set of stocks that catch their attention. While any given investor's attention may be caught by an idiosyncratic event such as a remark made by a neighbor or a factory passed while driving, the systematic direction of investor attention is mediated by the media.

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Table 1: Descriptive Statistics

Each day we compute the number of small and large buyer and seller initiated trades for the ISSM/TAQ 1983-2000 data and the number of retail buys and sells for the 2007-2017 data. We then compute the buy-sell imbalance, BSI = (#Buys - #Sells) / (#Buys + #Sells), for that day. Panel A reports summary statistics based calculated from daily observations from 1983 to 2000. Small trades are for $5,000 or less (1991 dollars) or less; large trades are for $50,000 or more (1991 dollars). Panel B reports summary statistics calculated from daily observations from 2007-2017.

Variable	N (Days)	Mean	Std. Dev.	Min	p25	p50	p75	Max
Panel A: 1983-2000 ISSM/TAQ								
Small Trades								
Number of Buys	4687	100.49	173.91	1.32	15.76	33.57	74.28	1038.36
Number of Sells	4687	97.08	170.73	1.21	15.94	27.97	67.21	1086.72
Buy-Sell Imbalance	4687	2.89%	8.41%	-38.94%	-1.84%	3.76%	8.50%	41.18%
Large Trades								
Number of Buys	4687	40.44	44.00	1.12	12.35	20.57	54.54	292.17
Number of Sells	4687	36.51	39.85	1.00	10.92	18.99	50.20	286.43
Buy-Sell Imbalance	4687	5.12%	7.66%	-34.74%	1.04%	5.06%	9.23%	37.80%
Panel B: 2007-2017 TAQ								
Retail Trades								
Number of Buys	2768	576.50	200.01	79.10	496.41	599.13	708.18	1555.10
Number of Sells	2768	547.66	185.72	83.38	474.09	569.83	664.95	1523.12
Buy-Sell Imbalance	2768	2.25%	3.95%	-18.05%	0.07%	2.63%	4.83%	17.57%

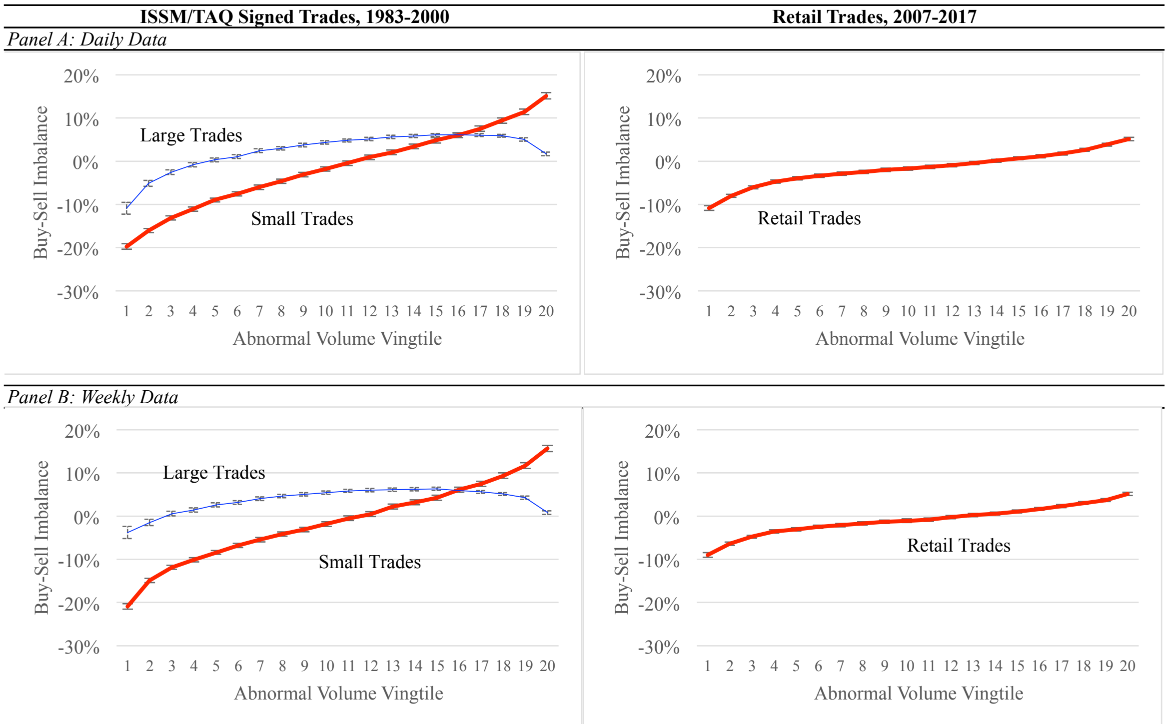

Figure 1: Buy-Sell Imbalance based on Abnormal Volume Sorts
In each week (Panel A) or day (panel B), stocks are sorted into 20 groups based on their abnormal trading volume during the period. During the same period as the sort, we calculate the buy-sell imbalance as the number of buys less the number of sells divided by the sum of buys and sells across all stocks within the abnormal volume sort. The two figures in the left column are based on large (blue) or small (red) trades based on ISSM/TAQ data from 1983-2000. The two figures on the right column are based on the identification of retail trades in the TAQ data from 2007-2017. Time series mean Buy-Sell Imbalances are graphed together with 95% confidence intervals.

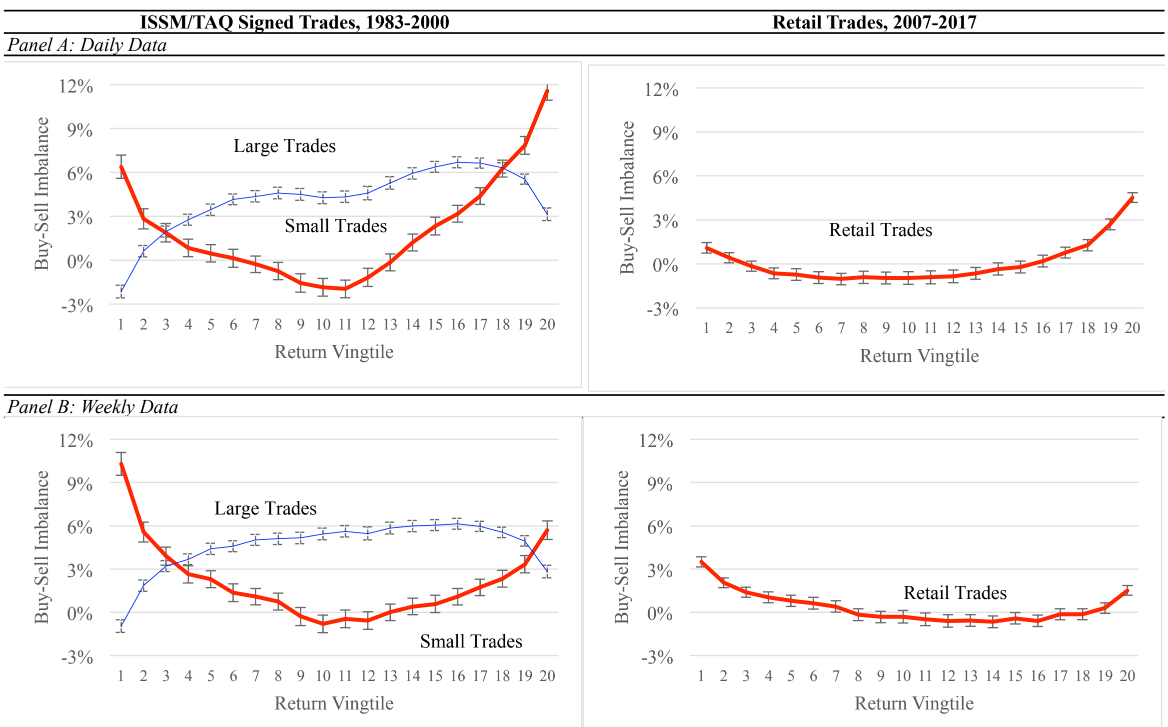

Figure 2: Buy-Sell Imbalance based on Return Sorts
In each week (Panel A) or day (panel B), stocks are sorted into 20 groups based on their returns in the preceding period. During the next period after the sort, we calculate the buy-sell imbalance as the number of buys less the number of sells divided by the sum of buys and sells across all stocks within the return sort. The two figures in the left column are based on large (blue) or small (red) trades based on ISSM/TAQ data from 1983-2000. The two figures on the right column are based on the identification of retail trades in the TAQ data from 2007-2017. Time series mean Buy-Sell Imbalances are graphed together with 95% confidence intervals.

ISSM/TAQ Signed Trades, 1983-2000

Panel A: Daily Data *Panel B: Weekly Data*

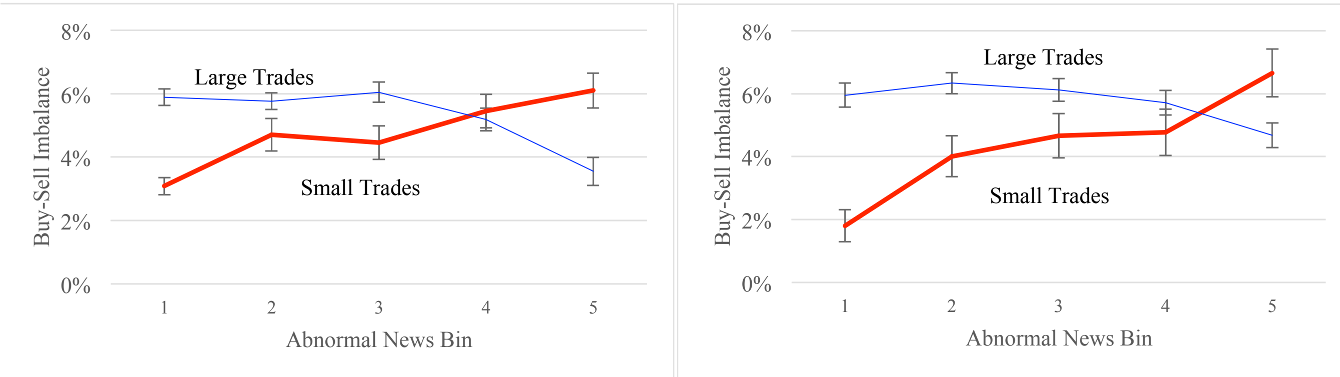

Figure 3: Buy-Sell Imbalance based on Abnormal News Sorts

In each week (Panel A) or day (panel B), stocks are sorted into 5 groups based on their abnormal news in the period. The abnormal news measure is computed as the number of news stories in the current week (or day) divided by the average number of weekly (or daily) news stories during the reference period from week -54 to week -5 (or from day -270 to day -21). A minimum of 10 weeks (or days) with news during the reference period is required. Stocks with no news in the current week or day are assigned to bin 0. Remaining stocks are sorted into quartiles on abnormal news measure, and are assgined to bins 2 (low abnormal news), 3, 4, and 5 (high abnormal news). In the same period as the sort, we calculate the buy-sell imbalance as the number of buys less the number of sells divided by the sum of buys and sells across all stocks within the abnormal news sort. The two figures are based on large (blue) or small (red) trades based on ISSM/TAQ data from 1983-2000. Time series mean Buy-Sell Imbalances are graphed together with 95% confidence intervals.

TAQ Signed Trades, 10/01/1997 - 12/31/1998

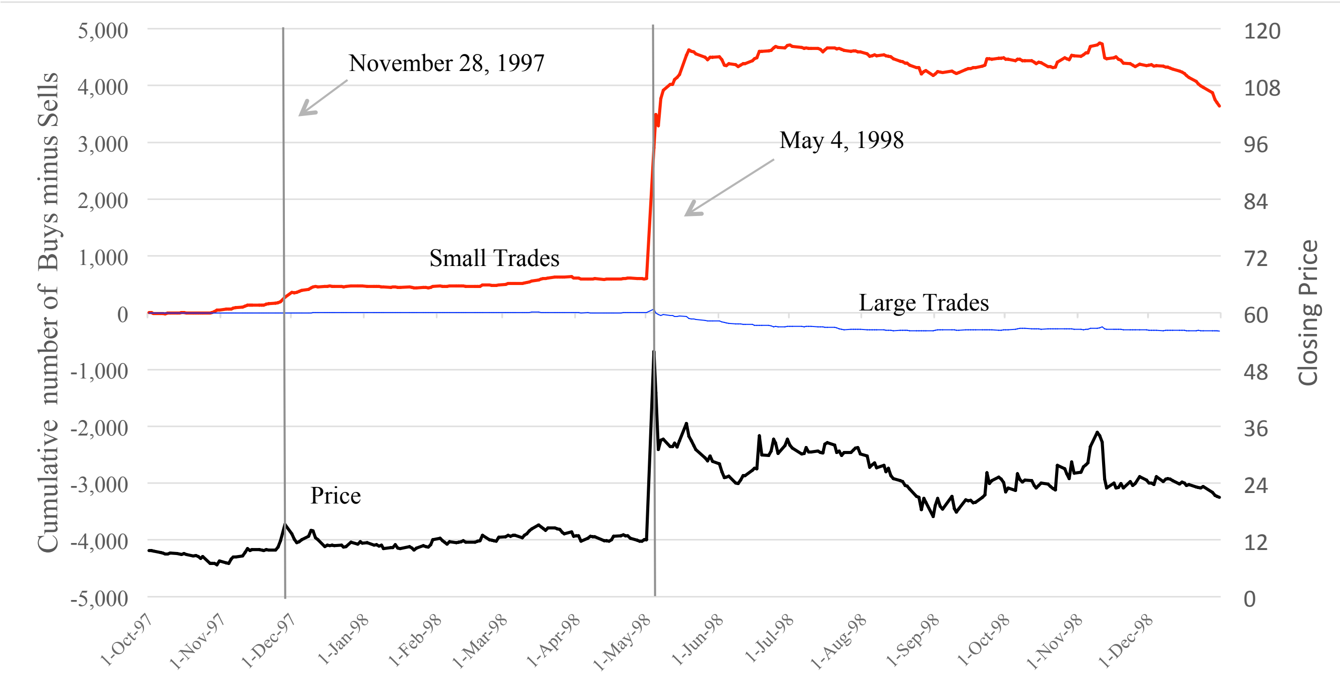

Figure 4: Cumulative Number of Small Buys minus Small Sells for EntreMed

The cummulative number of small (large) buyer initiated trades in EntreMed minus small (large) seller initiated trades beginning Oct. 1, 1997 (left axis). Daily closing price of EntreMed (right axis).

ISSM/TAQ Signed Trades, 1988-2000

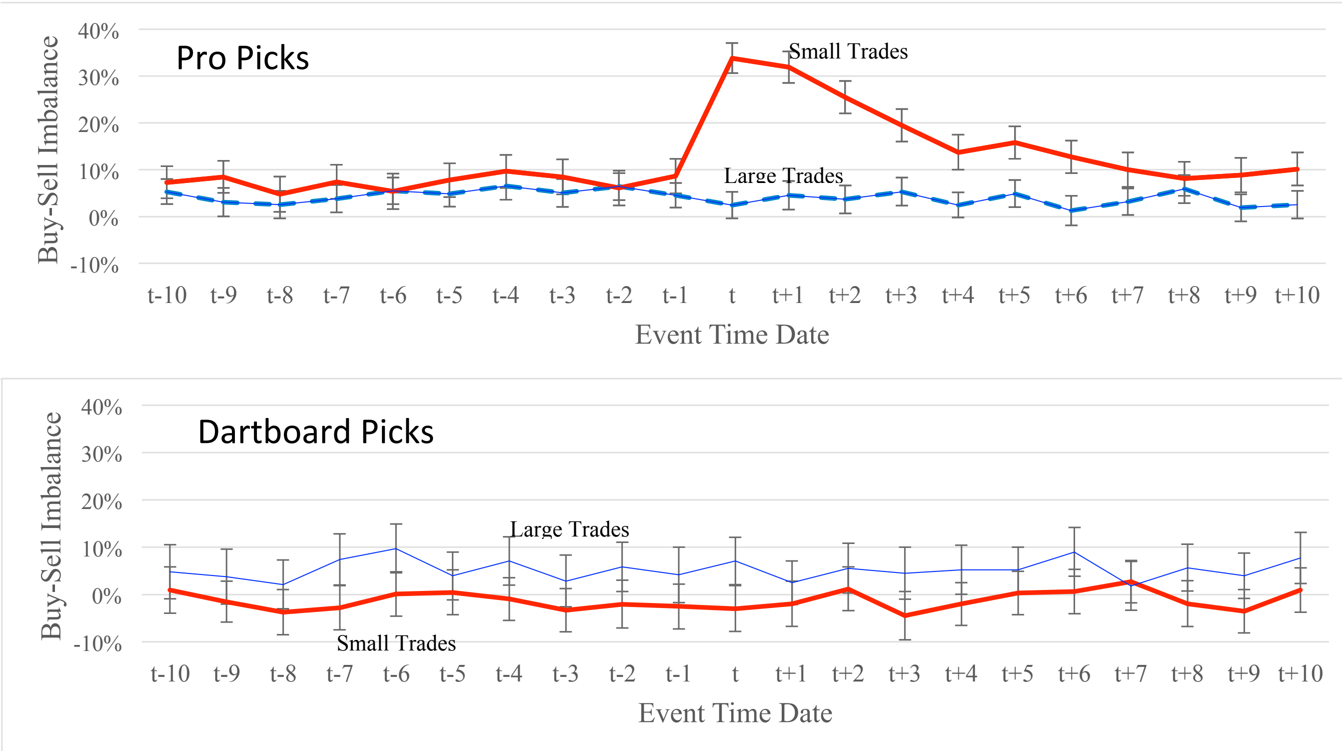

Figure 5: Buy-Sell Imbalance on Dartboard Column Stocks
The buy-sell imbalances, small and large, are reported on stocks by the Dartboard column of Wall Street Journal. The sample covers 145 columns during Oct. 4, 1988 and Dec. 14, 2000, which include 480 stocks under Pro Picks and 475 stocks under Dartboard Picks. A minimum of 10 trades per stock-day is required when computing buy-sell imbalances. Buy-sell imbalances are reported on each day of the event window [t-10, t+10]. Mean buy-sell imbalances and 95% confidence intervals are graphed for each event-time day.

TAQ Retail Trades, 2007-2017

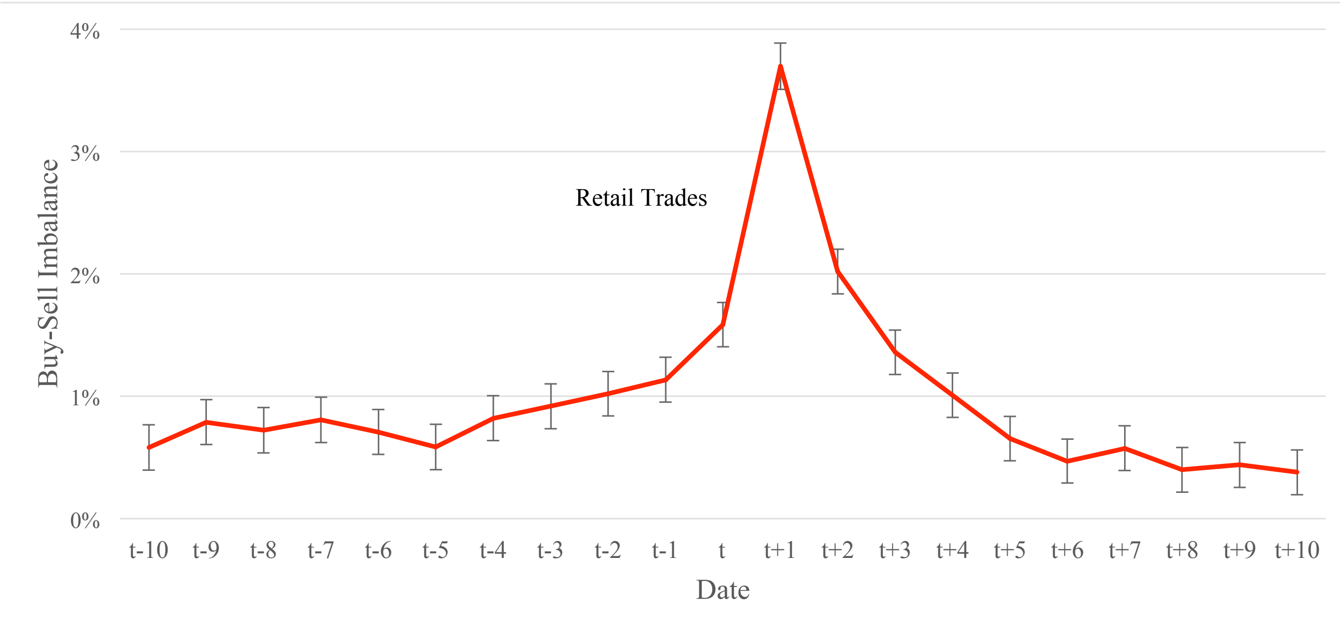

Figure 6: Buy-Sell Imbalances based on Mad Money covered Stocks
The buy-sell imbalances, small and large, are reported on stocks by the CNBC's TV show Mad Money. The sample covers 42,439 stock recommendations from 2007 to 2017 (only including US domestic stocks with share code 10 or 11). A minimum of 10 trades per stock-day is required when computing buy-sell imbalances. Mean Buy-sell imbalances and 95% confidence intervals are reported for each day of the event window [t-10, t+10].

TAQ Retail Trades, 2007-2017

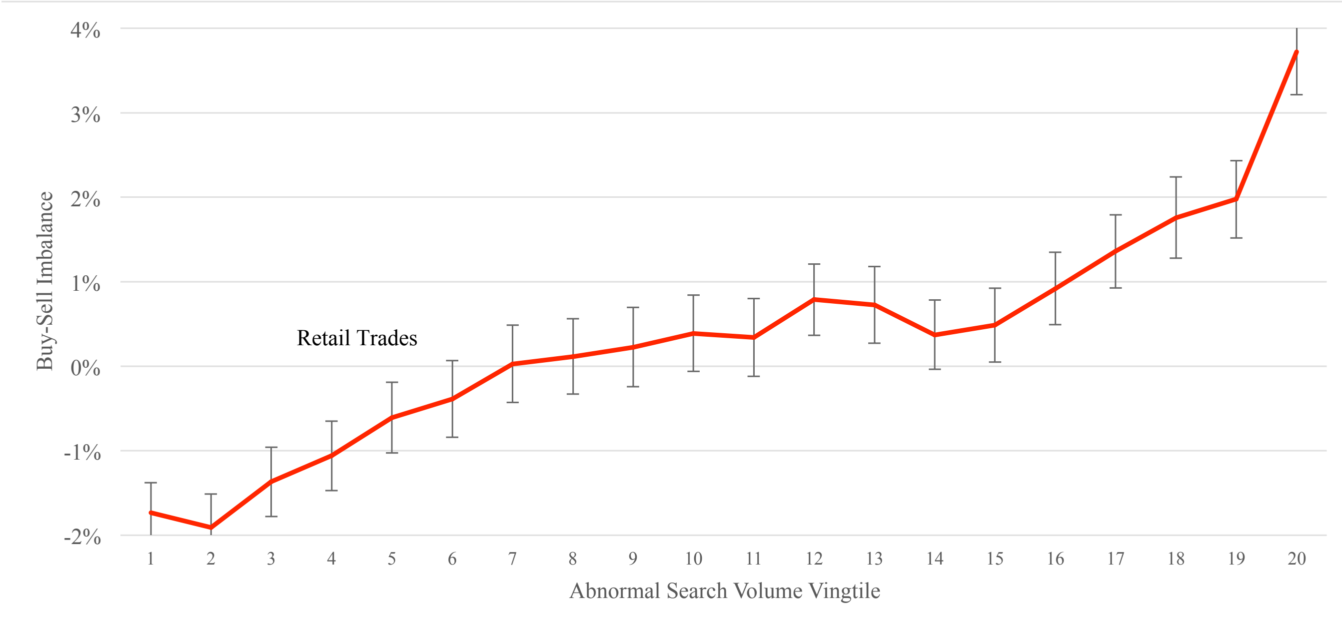

Figure 7: Buy-Sell Imbalances based on Abnormal Google Search Volume
A week starts on Sunday and ends on Saturday. Weekly search volume information is collected from Google Trends. In each week, the stocks (excluding the bottom 10% stocks in the previous year end's market capitalizations) are sorted into 20 vingtiles based upon abnormal search volume index (ASVI). ASVI is defined as the logarithm of a stock's current week's search volume index minus the median of the logarithm of each of the preceding 8 weeks' search volume indicies. During the same period as the sort, we calculate the buy-sell imbalance as the number of buys less the number of sells divided by the sum of buys and sells across all stocks within the abnormal search volume sort. The buy-sell imbalances are based on the identification of retail trades in the TAQ data from 2007-2017. Time series mean Buy-Sell Imbalances are graphed together with 95% confidence intervals.