All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors

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We test and confirm the hypothesis that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one-day returns. Attention-driven buying results from the difficulty that investors have searching the thousands of stocks they can potentially buy. Individual investors do not face the same search problem when selling because they tend to sell only stocks they already own. We hypothesize that many investors consider purchasing only stocks that have first caught their attention. Thus, preferences determine choices after attention has determined the choice set.

You have time to read only a limited number of research papers. How did you choose to read this paper? Investors have time to weigh the merits of only a limited number of stocks. Why do they consider some stocks and not others?

In making a decision, we first select which options to consider and then decide which of those options to choose. Attention is a scarce resource. When there are many alternatives, options that attract attention are more likely to be considered, hence more likely to be chosen, while options that do not attract attention are often ignored. If the salient attributes of an option are critical to our utility, attention may serve us well. If not, attention may lead to suboptimal

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choices. In this paper, we test the proposition that individual investors are more likely to buy rather than sell those stocks that catch their attention. We posit that this is so because attention affects buying—where investors search across thousands of stocks—more than selling—where investors generally choose only from the few stocks that they own. While each investor does not buy every single stock that grabs his attention, individual investors are more likely to buy attention-grabbing stocks than to sell them. We provide strong evidence that this is the case.

In contrast to our findings, many theoretical models of financial markets treat buying and selling as two sides of the same coin. Informed investors observe the same signal whether they are deciding to buy or to sell. They are equally likely to sell securities with negative signals as they are to buy those with positive signals. Uninformed noise traders are equally likely to make random purchases or random sales. In formal models, the decisions to buy and to sell often differ only by a minus sign.[1] For actual investors, the decisions to buy and to sell are fundamentally different.

When buying a stock, investors are faced with a formidable search problem. There are thousands of common stocks from which to choose. Human beings have bounded rationality. There are cognitive—and temporal—limits to how much information we can process. We are generally not able to rank hundreds, much less thousands, of alternatives. Doing so is even more difficult when the alternatives differ on multiple dimensions. One way to make the search for stocks to purchase more manageable is to limit the choice set. It is far easier, for example, to choose among ten alternatives than a hundred.

Odean (1999) proposes that investors manage the problem of choosing among thousands of possible stock purchases by limiting their search to stocks that have recently caught their attention. Investors do not buy all stocks that catch their attention; however, for the most part, they only buy stocks that do so. Which attention-grabbing stocks investors buy will depend upon their personal preferences. Contrarian investors, for example, will tend to buy out-of-favor stocks that catch their eye, while momentum investors will chase recent performers.

While, in theory, investors face the same search problem when selling as when buying, in practice, two factors mitigate the search problem for individual investors when they want to sell. First, most individual investors hold relatively few common stocks in their portfolio.[2] Second, most individual investors sell only stocks that they already own—that is, they do not sell short.[3] Thus, investors can, one by one, consider the merits—both economic and emotional—of selling each stock they own. Rational investors are likely to sell their past

[1] For example, see the well-cited models of Grossman and Stiglitz (1980) and Kyle (1985).

[2] During our sample period, the mean household in our large discount brokerage dataset held a monthly average of 4.3 stocks worth $47,334; the median household held a monthly average of 2.61 stocks worth $16,210.

[3] 0.29% of positions are short positions for the investors in the large discount brokerage dataset that we describe in Section 2. When the positions are weighted by their value, 0.78% are short.

losers, thereby postponing taxes; behaviorally motivated investors are likely to sell past winners, thereby postponing the regret associated with realizing a loss (see Shefrin and Statman, 1985); thus, to a large extent, while individual investors are concerned about the future returns of the stocks they buy, they focus on the past returns of the stocks they sell.

Our argument that attention is a major factor determining the stocks individual investors buy, but not those they sell, does not apply with equal force to institutional investors. There are two reasons for this: (i) Unlike individual investors, institutions often face a significant search problem when selling. Institutional investors, such as hedge funds, routinely sell short. For these investors, the search set for purchases and sales is identical. And even institutions that do not sell short face far more choices when selling than do most individuals, simply because they own many more stocks than do most individuals. (ii) Attention is not as scarce a resource for institutional investors as it is for individuals. Institutional investors devote more time to searching for stocks to buy and sell than do most individuals. Institutions use computers to narrow their search. They may limit their search to stocks in a particular sector (e.g., biotech) or meeting specific criteria (e.g., low price-to-earnings ratio), thus reducing attention demands. Though individuals can also use computers or preselection criteria, on average they are less likely to do so.

In this paper, we test the hypotheses that (i) the buying behavior of individual investors is more heavily influenced by attention than is their selling behavior and that (ii) the buying behavior of individual investors is more heavily influenced by attention than is the buying behavior of professional investors.

How can we measure the extent to which a stock grabs investors' attention? A direct measure would be to go back in time and, each day, question the hundreds of thousands of investors in our datasets as to which stocks they thought about that day. Since we cannot measure the daily attention paid to stocks directly, we do so indirectly. We focus on three observable measures that are likely to be associated with attention-grabbing events: news, unusual trading volume, and extreme returns. While none of these measures is a perfect proxy for attention, all three are useful.

An attention-grabbing event is likely to be reported in the news. Investors' attention could be attracted through other means, such as chat rooms or word of mouth, but an event that attracts the attention of many investors is usually newsworthy. However, news stories are not all created equal. Major network reporting of the indictment of a Fortune 500 CEO will attract the attention of millions of investors, while a routine company press release may be noticed by few. Our historical news data—from the Dow Jones News Service—do not tell us how many investors read each story, nor do they rank each story's importance. We infer the reach and impact of events by observing their effects on trading volume and returns.

Trading volume in the firm's stock is likely to be greater than usual when news about a firm reaches many investors. Of course, this won't necessarily be the case. Investors will possibly recognize this news to be irrelevant to the firm's future earnings and not trade, or investors will all interpret the news similarly and not trade. But significant news will often affect investors' beliefs and portfolio goals heterogeneously, resulting in more investors trading than is usual. If an unusual number of investors trade a stock, it is nearly tautological that an unusual number are paying attention to that stock. But high abnormal trading volume could also be driven by the liquidity or information-based trades of a few large investors. Our results are as strong, or stronger, for large capitalization stocks. Unusual trading volume for these stocks is unlikely to be driven by only a few investors. Therefore, large trades by a few investors may add noise to our calculations, but are unlikely to be driving the results.

Important news about a firm often results in significant positive or negative returns. Some news may be difficult to interpret and result in unusually active trading without much price change. But when there is a big price move, it is likely that whatever caused the move also caught investors' attention. And even when price is responding to private, not public, information, significant returns will often, in and of themselves, attract attention.

Our three proxies for whether investors were paying attention to a firm are: (i) a stock's abnormal daily trading volume; (ii) the stock's (previous) one-day return;[4] and (iii) whether the firm appeared in that day's news. We examine the buying and selling behavior associated with attention for four samples of investors:

- investors with accounts at a large discount brokerage,
- investors at a smaller discount brokerage firm that advertises its trade execution quality,
- investors with accounts at a large retail brokerage, and
- professional money managers.

Our prediction is that individual investors will actively buy stocks on high-attention days. We are not predicting that they will actively trade on high-attention days—that would hardly be surprising when we use abnormal trading volume as a proxy for attention—rather, that they will be net buyers.

For every buyer, there must be a seller. Therefore, on days when attention-driven investors are buying, some investors, whose purchases are less dependent on attention, must be selling. We anticipate therefore, that professional investors as a whole (inclusive of market-makers) will exhibit a lower tendency to buy, rather than sell, on high-attention days and a reverse tendency on low-attention days. (Exceptions will arise when the event driving attention coincides with the purchase criteria that a particular professional investor is pursuing.)

As predicted, individual investors tend to be net buyers on high-attention days. For example, investors at the large discount brokerage make nearly twice

[4] We use previous-day return, rather than same-day return, because of potential endogeneity problems. While we argue that extreme price moves will attract buyers, clearly, buyers could also cause price moves. Our results are qualitatively similar when we use same-day returns as a proxy for attention.

as many purchases as sales of stocks experiencing unusually high trading volume (e.g., the highest 5%)[5] and nearly twice as many purchases as sales of stocks with an extremely poor return (lowest 5%) the previous day. The buying behavior of the professionals is least influenced by attention.

The plan of the paper is as follows. We discuss related research in Section 1. We describe the four datasets in Section 2 and our sorting methodology in Section 3. We present evidence of attention-driven buying in Section 4 and discuss an alternative hypothesis in Section 5. We conclude in Section 6 and present a formal model of attention-driven buying in the Appendix.

1. Related Research

A number of recent studies examine investor-trading decisions. Odean (1998a) finds that, as predicted by Shefrin and Statman (1985), individual investors exhibit a disposition effect—investors tend to sell their winning stocks and hold on to their losers. Both individual and professional investors have been found to behave similarly with several types of assets, including real estate (Genesove and Mayer, 2001), company stock options (Heath, Huddart, and Lang, 1999), and futures (Heisler, 1994; Locke and Mann, 2000) (also see Shapira and Venezia, 2001).

It is well documented that volume increases on days with information releases or large price moves (Bamber, Barron, and Stober, 1997; Karpoff, 1987). For example, when Maria Bartiromo mentions a stock during the Midday Call on CNBC, volume in the stock increases nearly five fold (on average) in the minutes following the mention (Busse and Green, 2002). Yet, for every buyer, there is a seller. In general, these studies do not investigate who is buying and who is selling, which is the focus of our analysis. One exception is Lee (1992). He examines trading activity around earnings announcements for 230 stocks over a one-year period. He finds that small traders—those who place market orders of less than $10,000—are net buyers subsequent to both positive and negative earnings surprises. Hirshleifer et al. (2003) document that individual investors are net buyers following *both* positive and negative earnings surprises. Lee (1992) conjectures that news may attract investors' attention or, alternatively, that retail brokers—who tend to make more buy than sell recommendations—may routinely contact their clients around the time of earnings announcements. In a recent paper, Huo, Peng, and Xiong (2006) argue that high individual investor attention can exacerbate price overreactions in up markets while attenuating underreactions to events such as earnings reports.

Odean (1999) examines trading records of investors at a large discount brokerage firm. He finds that, on average, the stocks these investors buy underperform those they sell, even before considering transactions costs. He

[5] Looking at all common stock transactions, investors at this brokerage make slightly more purchases (1,082,107) than sales (887,594).

observes that these investors buy stocks that have experienced greater absolute price changes over the previous two years than the stocks they sell. He points out the search problem individual investors face when choosing from among thousands of stocks and the disparity between buying and selling decisions for individual investors. He suggests that many investors limit their search to stocks that have recently captured their attention, with contrarians buying previous losers and trend chasers buying previous winners.

Of course, fully rational investors will recognize the limitations of buying predominantly stocks that catch their attention. They will realize that the information associated with an attention-grabbing event may already be impounded into price (since the event has undoubtedly been noticed by others), that the attention-grabbing event may not be relevant to future performance, and that nonattention-grabbing stocks may present better purchase opportunities. Odean (1998b) argues that many investors trade too much because they are overconfident about the quality of their information. Such investors may overvalue the importance of events that catch their attention, thus leading them to trade suboptimally. Odean (1999) and Barber and Odean (2000, 2001, 2002) find that, on average, self-directed individual investors do trade suboptimally, lowering their expected returns through excessive trading.

In recent work, Seasholes and Wu (2004) test our theory in a unique out-of-sample setting. They observe that on the Shanghai Stock Exchange, individual investors are net buyers the day after a stock hits an upper price limit. Furthermore, they document that a higher percentage of purchases is made by first-time buyers on price limit days than on other days. Seasholes and Wu's interpretation of this behavior is that the attention of individual investors, especially first-time buyers, is attracted by the event of hitting a price limit and, consistent with our theory, individuals become net buyers of stocks that catch their attention. Also consistent with our theory, Seasholes and Wu document a transitory impact on prices with reversion to pre-event levels within ten trading days. Finally, they identify a small group of professional investors who profit—at the expense of individual investors—by anticipating this temporary surge in price and demand.

Our analysis focuses on investor trading patterns over one-day periods. With our proxies for attention, we try to identify days on which an unusual event appears to have attracted investors' attention to a particular firm's stock. Like unusual events, advertising may also increase investors' awareness of a firm. Grullon, Kanatas, and Weston (2004) document that firms that spend more on advertising have a larger number of individual and institutional investors. They argue that a firm's advertising increases investors' familiarity with the firm and that investors are more likely to own familiar firms. Their paper differs from ours in many respects. They look at annual advertising budgets; we identify daily attention-grabbing events. They focus on dispersion of ownership; we, on daily trading patterns. Both papers are consistent with a common story in which investors are more likely to buy—and therefore own—stocks that have attracted their attention, whether through unusual events or extensive advertising.

Gervais, Kaniel, and Mingelgrin (2001) find that stocks experiencing unusually high trading volume over a day or a week tend to appreciate over the following month. Citing Miller (1977) and Mayshar (1983), they argue that the holders of a stock will tend to be those who are most optimistic about its prospects and that, given institutional constraints on short-selling, any increase in the set of potential owners (potential buyers) should result in a price increase. The increased visibility of a stock associated with high-trading volume increases the set of potential owners (buyers) but not of potential sellers, resulting in a price increase.

Alternatively, Merton (1987) notes that individual investors tend to hold only a few different common stocks in their portfolios. He points out that gathering information on stocks requires resources and suggests that investors conserve these resources by actively following only a few stocks. If investors behave this way, they will buy and sell only those stocks that they actively follow. They will not impulsively buy stocks that they do not follow simply because those stocks happen to catch their attention. Thus, their purchases will not be biased toward attention-grabbing stocks.

While Grullon, Kanatas, and Weston (2004) focus on the number of individuals and institutions that own a stock and Gervais et al. (2001) focus on returns subsequent to high- (or low-) volume periods, our principal empirical focus is on the effect of attention on the imbalance in the number of purchases and sales of a stock by individual investors. Our empirical finding that individual investors are net buyers of attention-grabbing stocks is largely consistent with the empirical results in Grullon, Kanatas, and Weston (2004). This finding is also consistent with the story of Gervais, Kaniel, and Mingelgrin (2001) that increased visibility of a stock may attract new investors. In addition to the effects of attention driven by short-sale constraints as described by Miller (1977) and Mayshar (1983), we argue that for individual investors, the search problem when buying a stock is much greater than when selling. Thus, attention affects even the buy-sell imbalances of investors who already own a stock.

2. Data

In this study, we analyze investor trading data drawn from four sources: a large discount brokerage, a small discount brokerage, a large full-service brokerage, and the Plexus Group—a consulting firm that tracks the trading of professional money managers for institutional clients.

The first dataset for this research was provided by a large discount brokerage firm. It includes trading and position records for the investments of 78,000 households from January 1991 through December 1996.[6] The data include all

[6] Position records are through December 1996; trading records are through November 1996. See Barber and Odean (2000) for a more compete description of these data.

accounts opened by each household at this discount brokerage firm. Sampled households were required to have an open account with the discount brokerage firm during 1991. Roughly half of the accounts in our analysis were opened prior to 1987, and half were opened between 1987 and 1991.

In this research, we focus on investors' common stock purchases and sales. We exclude from the current analysis investments in mutual funds (both open- and closed-end), American depository receipts (ADRs), warrants, and options. Of the 78,000 households sampled from the large discount brokerage, 66,465 had positions in common stocks during at least one month; the remaining accounts held either cash or investments other than individual common stocks. Roughly 60% of the market value in these households' accounts was held in common stocks. There were more than three million trades in all securities; common stocks accounted for slightly more than 60% of all trades. In December 1996, these households held more than $4.5 billion in common stock. There were slightly more purchases (1,082,107) than sales (887,594) during our sample period, though the average value of stocks sold ($13,707) was slightly higher than the value of stocks purchased ($11,205). As a result, the aggregate values of purchases and sales were roughly equal ($12.1 and $12.2 billion, respectively). The average trade was transacted at a price of $31 per share. The value of trades and the transaction price of trades are positively skewed; the medians for both purchases and sales are substantially less than the mean values.

Our second dataset contains information from a smaller discount brokerage firm. This firm emphasizes high-quality trade execution in its marketing and is likely to appeal to more sophisticated, more active investors. The data include daily trading records from January 1996 through 15 June 1999. Accounts classified by the brokerage firm as professionals are excluded from our analysis.[7] The data include 14,667 accounts for individual investors who make 214,273 purchases with a mean value of $55,077 and 198,541 sales with a mean value of $55,999.

The third dataset contains information from a large retail brokerage firm on the investments of households for the 30 months ending in June 1999. These data include daily trading records. Using client ownership codes supplied by the brokerage firm, we limit our analysis to the 665,533 investors with nondiscretionary accounts (i.e., accounts classified as individual, joint tenants with rights of survival, or custodian for minor) with at least one common stock trade during our sample period. During this period, these accounts executed more than 10 million trades. We restrict our analysis to their common stock trades: 3,974,998 purchases with a mean value of $15,209 and 3,219,299 sales with a mean value of $21,169.[8]

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[7] We analyze the accounts of professional investors separately. There are, however, only 159 professional traders in these data, and we do not observe clear patterns in their buy-sell imbalances.

[8] Barber, Odean, and Zhu (2006) analyze the correlation of the first and third broker datasets with trades in the TAQ/ISSM database. Specifically, in the TAQ/ISSM data, they identify small trades (less than $5000 in

Our individual investor data include tens of thousands of investors at both discount and retail brokerages. These data are likely to be fairly representative of U.S. individual investors.[9] Our institutional data, however, are more illustrative than representative of institutional investors. The data were compiled by the Plexus Group as part of their advisory services for their institutional clients. The data include daily trading records for 43 institutional money managers and span the period January 1993 through March 1996. Not all managers are in the sample for the entire period. In addition to documenting completed purchases and sales, the data also report the date and time at which the manager decided to make a purchase or sale. In the data, these money managers are classified as "momentum," "value," and "diversified."[10] During our sample period, the 18 momentum managers make 789,779 purchases with a mean value of \$886,346 and 617,915 sales with a mean value of \$896,165; the 11 value managers make 409,532 purchases with a mean value of \$500,949 and 350,200 sales with a mean value of \$564,692; the 14 diversified managers make 312,457 purchases with a mean value of \$450,474 and 202,147 sales with a mean value of \$537,947.

3. Sort Methodology

3.1 Volume sorts

On the days when a stock experiences abnormally heavy volume, it is likely that investors are paying more attention to it than usual. We wish to test the extent to which the tendency to buy stocks increases on days of unusually high trading volume for each of our four investor groups (large discount, retail, small discount, and professional). First, we must sort stocks on the basis of abnormal trading volume. We do so by calculating for each stock on each trading day 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). Thus, we define abnormal trading volume for stock i on day t, $AV_{it}$to be

$$AV_{it} = \frac{V_{it}}{\bar{V}_{it}}, \tag{1}$$

1991 dollars) that are buyer-initiated and seller-initiated. They then calculate monthly buy-sell imbalance for each stock/month using these trades. In each month with overlapping data, they calculate the cross-sectional correlation between the buy-sell imbalance of small trades on the TAQ database and the buy-sell imbalance of the broker data. For the large discount broker, the mean correlation is 55%. For the large retail broker, the mean correlation is 43%.

9 Wolff (2004) reports that over one-third of stock ownership—including direct ownership of shares and indirect ownership through mutual funds, trusts, and retirement accounts—of U.S. households is concentrated in the wealthiest 1% of households. The portfolios of extremely wealthy families are unlikely to appear in our sample and constitute a third class of investors in addition to ordinary individuals and institutional investors. The portfolios of wealthy families are usually professionally managed and, as such, we would expect them to be traded more like institutional portfolios than like the portfolios of ordinary individual investors.

10 Keim and Madhavan (1995, 1997, and 1998) analyze earlier data from the Plexus Group. They classify managers as "technical," "value," and "index." Based on conversations with the Plexus Group, we believe that these classifications correspond to our "momentum," "value," and "diversified" classifications.

where V_{it} is the dollar volume for stock i traded on day t as reported in the Center for Research in Security Prices (CRSP) daily stock return files for New York Stock Exchange (NYSE), American Stock Exchange (ASE), and NASDAQ stocks and

$$\bar{V}_{it} = \sum_{d=t-252}^{t-1} \frac{V_{id}}{252}. \tag{2}$$

Each day, we sort stocks into deciles on the basis of that day's abnormal trading volume.[11] We further subdivide the decile of stocks with the greatest abnormal trading volume into two vingtiles (i.e., 5% partitions). Then, for each of our investor types, we sum the buys (B) and sells (S) of stocks in each volume partition on day t and calculate the buy-sell imbalance for purchases and sales executed that day as

$$BSI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}}, \tag{3}$$

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 imbalances (BSI_{pt}) for the days that we have trading data for each investor type. Note that throughout the paper, our measure of buy-sell imbalance considers only executed trades; limit orders are counted if and when they execute. If there are fewer than five trades in a partition on a particular day, that day is excluded from the time series average for that partition. We also calculate buy-sell imbalances based on the value rather than number of trades by substituting in the value of the stock i bought (or sold) on day t for NB_{it} (or NS_{it}) in Equation (3). Note that as trading volume increases, aggregate buying and selling will increase equally. Thus, the aggregate value-weighted (executed) buy-sell imbalance of all investors remains zero as abnormal volume increases, but how the buy-sell imbalance of a particular investor group changes with volume is an empirical question.

In summary, for each partition and investor group combination, we construct a time series of daily buy-sell imbalances. Our inferences are based on the mean and standard deviation of the time series. We calculate the standard deviation of the time series using a Newey-West correction for serial dependence.

[11] In auxiliary analyses, we calculate volume partitions that use (i) the measure of abnormal volume employed by Gervais, Kaniel, and Mingelgrin (2001) and (ii) a standardized measure of abnormal volume: $(V - \overline{V})/\sigma$, where V is volume on day t, $\overline{V}$ is mean volume over the prior 252 trading days, and σ is the standard deviation of volume over the prior 252 trading days. We also analyze abnormal volume measures as the ratio of volume on day t to mean volume over the prior 50 days. All alternative measures of abnormal volume generate buy-sell imbalance patterns that are very similar to those using our simple measure of buy-sell imbalance: $(V/\overline{V})$. These results are available from the authors at http://faculty.haas.berkeley.edu/odean/attention.html.

3.2 Return sorts

Investors are likely to notice when stocks have extreme one-day returns. Such returns, whether positive or negative, often will be associated with news about the firm. The news driving the extreme performance will catch the attention of some investors, while the extreme return itself will catch the attention of others. Even in the absence of other information, extreme returns can become news themselves. The *Wall Street Journal* and other media routinely report the previous day's big gainers and losers (subject to certain price criteria). If big price changes catch investors' attention, then we expect that those investors whose buying behavior is most influenced by attention will tend to purchase in response to price changes—both positive and negative. To test the extent to which each of our four investor groups are net purchasers of stocks in response to large price moves, we sort stocks based on one-day returns and then calculate average buy-sell imbalances for the following day. We calculate imbalances for the day following the extreme returns, rather than the same day as extreme returns, for two reasons. First, many investors may learn of—or react to—the extreme return only after the market closes; their first opportunity to respond will be the next trading day. Second, buy-sell imbalances could cause contemporaneous price changes. Thus, examining buy-sell imbalances subsequent to returns removes a potential endogeneity problem.[12] Our results are qualitatively similar when we sort on same-day returns.

For each day, $(t-1)$, we sort all stocks for which returns are reported in the CRSP NYSE/AMEX/NASDAQ daily returns file into 10 deciles based on the one-day return. We further split decile 1 (lowest returns) and decile 10 (highest returns) into two vingtiles. We then calculate the time series mean of the daily buy-sell imbalances for each partition on the day following the return sort. This calculation is analogous to that for our sorts based on abnormal volume.[13]

[12] Endogeneity does not pose the same problem for news and abnormal volume sorts. It is unlikely that the percentage of individual investors' (or institutional investors') trades that consists of purchases causes contemporaneous news stories. Nor is it likely that the percentage of individual investors' (or institutional investors') trades that consists of purchases causes abnormal trading volume. As a robustness check on the latter point, we replicate our results by calculating abnormal volume on day t and analyzing buy-sell imbalance on day $t+1$. Our results are qualitatively similar to those reported in the paper and are available from the authors at http://faculty.haas.berkeley.edu/odean/attention.html.

[13] Typically, a significant number of stocks have a return equal to zero on day $t-1$. These stocks may span more than one partition. Therefore, before calculating the buy-sell imbalance for each partition, we first calculate the average number (and value) of purchases and sales of stocks with returns of zero on day $t-1$; in subsequent calculations, we use this average number (and value) of purchases and sales for zero-return stocks. The average number of purchases on day t of a stock with a return of zero on day $t-1$ is

$$\sum_{s=1}^{S_0} \frac{NB_{St}}{S_0},$$

where NB_{St} is the number of times stock s was purchased by investors in the dataset on day t and S_0 is the number of stocks with a return of zero on day $t-1$. Similar calculations are done to determine the average number of sales and the average value of purchases and sales for stocks with a return of zero on day $t-1$. We also have replicated our results using standardized returns. Specifically, on each day, we calculate $(R)/\sigma$, the daily return on day t divided by the standard deviation of the firm's daily return from $t-252$ to $t-1$. Results using the standardized measure of returns are similar to those reported in the paper and are available from the authors at http://faculty.haas.berkeley.edu/odean/attention.html.

3.3 News sorts

Firms that are in the news are more likely to catch investors' attention than those that are not. Our news dataset is the daily news feed from Dow Jones News Service for the period 1994 to 1999. The Dow Jones news feed includes the ticker symbols for each firm mentioned in each article. We partition stocks into those for which there is a news story that day and those with no news. On an average day, our dataset records no news for 91% of the firms in the CRSP database. Due to how the data were collected and stored, some days are missing from the data. We calculate buy-sell imbalances for each firm's stock as described in Section 3.1. News is a primary mechanism for catching investors' attention. Nonetheless, our empirical tests based on news coverage lack the power of our volume and return sorts because we are unable to measure accurately the intensity or salience of news coverage, and we are missing news coverage data for much of our sample period.

It is worth noting that none of our proxies for attention is perfect. Some stocks appear in our news database because of news stories about significant attention-grabbing events; others appear simply because of routine company press releases. Similarly, abnormally high trading volume may be associated with active trading and attention of individual investors, or it may occur because institutional investors transact large trades with each other on days when individuals are not particularly attending to a stock. And large one-day price moves may be driven by attention-grabbing events, but they may also result from temporary liquidity shortages caused by an institutional investor selling or purchasing a large position. If our proxies identify attention-grabbing events much, or most, of the time, then in aggregate we expect individual investors to be on the buy side of the market on high-attention days as identified by our proxies.

4. Results

4.1 Volume sorts

Trading volume is one indicator of the attention a stock is receiving. Table 1 presents buy-sell imbalances for stocks sorted on the current day's abnormal trading volume. Buy-sell imbalances are reported for investors at a large discount brokerage, a large retail brokerage, and a small discount brokerage and for institutional money managers following momentum, value, and diversified strategies. Buy-sell imbalances are calculated using both the number of trades and the value of trades. Our principal objective is to understand how attention affects the purchase decisions of all investors. Calculating buy-sell imbalances by the value of trades has the advantage of offering a better gauge of the economic importance of our observations, but the disadvantage of overweighting the decisions of wealthier investors. In trying to understand investors' decision

Table 1
Buy-sell imbalances by investor type for stocks sorted on the current day's abnormal trading volume

	Large discount brokerage		Large retail brokerage		Small discount brokerage		Momentum managers		Value managers		Diversified managers	
Decile	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance
1 (lowest volume)	−18.15	−16.28	−25.26	−21.26	−20.49	−22.70	14.68	13.74	34.57	33.99	12.52	17.10
	(0.98)	(1.37)	(2.11)	(1.60)	(3.41)	(3.88)	(1.76)	(2.26)	(5.54)	(6.45)	(2.42)	(2.91)
2	−8.90	−11.32	−18.78	−20.63	−10.31	−11.02	12.13	11.09	15.20	13.63	14.87	15.06
	(0.65)	(0.98)	(1.23)	(1.30)	(2.30)	(2.47)	(1.07)	(1.44)	(2.35)	(2.91)	(1.62)	(1.97)
3	−6.23	−9.49	−15.16	−19.59	−6.95	−7.76	11.38	10.35	10.95	8.43	15.83	11.84
	(0.52)	(0.84)	(1.18)	(1.18)	(1.47)	(1.90)	(0.85)	(1.15)	(1.49)	(1.93)	(1.28)	(1.65)
4	−2.76	−8.70	−10.11	−20.07	−4.92	−5.91	12.19	11.89	10.02	4.37	14.92	8.23
	(0.45)	(0.73)	(0.99)	(1.29)	(1.17)	(1.56)	(0.81)	(1.07)	(1.23)	(1.61)	(1.09)	(1.50)
5	−0.76	−7.24	−4.82	−17.38	−4.06	−6.80	12.62	12.24	10.90	6.51	13.41	3.97
	(0.42)	(0.67)	(1.03)	(1.37)	(0.77)	(1.34)	(0.72)	(0.94)	(1.10)	(1.38)	(0.96)	(1.28)
6	1.65	−7.33	0.23	−16.23	−1.86	−3.33	13.54	13.95	8.73	0.31	12.58	3.31
	(0.42)	(0.64)	(1.01)	(1.17)	(0.81)	(1.05)	(0.70)	(0.92)	(1.03)	(1.32)	(0.90)	(1.23)
7	5.45	−2.87	6.69	−13.80	-0.05	−2.58	12.47	13.17	7.25	−0.61	10.99	−0.61
	(0.43)	(0.63)	(1.03)	(1.19)	(0.74)	(0.96)	(0.65)	(0.85)	(0.97)	(1.28)	(0.82)	(1.11)
8	9.20	−1.10	13.53	−7.92	1.43	−2.11	11.60	12.11	8.93	1.30	10.80	−0.19
	(0.41)	(0.62)	(1.14)	(1.16)	(0.79)	(0.86)	(0.64)	(0.87)	(0.95)	(1.25)	(0.84)	(1.21)
9	13.62	2.86	19.82	−2.02	5.78	1.36	11.33	8.90	7.83	1.09	11.11	3.47
	(0.43)	(0.62)	(1.27)	(1.21)	(0.62)	(0.91)	(0.62)	(0.93)	(1.01)	(1.40)	(0.89)	(1.32)
10a	17.72	6.97	22.25	2.62	8.90	3.67	10.84	7.57	7.72	6.38	11.04	5.58
	(0.51)	(0.75)	(1.46)	(1.24)	(0.83)	(1.07)	(0.81)	(1.22)	(1.46)	(2.04)	(1.20)	(1.93)
10b (highest volume)	29.50	17.67	19.34	2.02	17.31	11.78	6.72	−0.55	4.83	4.15	8.12	7.23
	(0.49)	(0.73)	(1.71)	(1.84)	(0.98)	(1.03)	(0.82)	(1.34)	(1.79)	(2.44)	(1.37)	(2.22)

Stocks are sorted daily into deciles of the basis of the current day's abnormal volume. The decile of the highest abnormal volume is split into two vingtiles (10a and 10b). Abnormal volume is calculated as the ratio of the current day's volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average volume over the previous 252 trading days. Buy-sell imbalances are reported for the trades of six groups of investors, investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through 15 June 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

processes, calculating buy-sell imbalances by number of trades may be the most appropriate.

Investors at the large discount brokerage display the greatest amount of attention-driven buying. When imbalances are calculated by number of trades (column 2), the buy-sell imbalance is −18.15% for stocks in the lowest volume decile. For stocks in the highest volume vingtile, the buy-sell imbalance is +29.5% more. Buy-sell imbalances for these investors rise monotonically with trading volume. When imbalances are calculated by value of trades (column 3), the buy-sell imbalance is −16.28% for stocks in the lowest volume decile. For stocks in the highest volume vingtile, the buy-sell imbalance is +17.67%. Again, buy-sell imbalances increase nearly monotonically with trading volume. Looking at columns 4–7 of Table 1, we see that the net buying behavior of investors at the large retail broker and the small discount brokerage behaves similarly to that of investors at the large discount brokerage.

In the Appendix, we present a theoretical model extending Kyle (1985). The model provides a rigorous framework in which to examine the implications of attention-driven buying. It enables us to simulate the trading of investors who are influenced by attention. The model also generates one testable asset pricing theorem. The focus of this paper is to introduce and test a novel theory of investor behavior, not to test the asset pricing impact of this behavior. In auxiliary analysis, we find evidence that investors do not benefit from attention-based buying and that attention-based buying may influence asset prices.[14] Figure 1a plots average buy-sell imbalances conditional on trading volume for 100,000 simulations based on our theoretical model. (See Appendix for simulation details.) Figure 2a plots buy-sell imbalances based on number of trades for investors at the large discount brokerage, the large retail brokerage, and the small discount brokerage. Note that the simulated and the empirical plots are both upward sloping. The simulation serves to illustrate that our empirical results are consistent with what we find in a simple model in which investors are assumed to engage in attention-driven buying.

The last six columns of Table 1 present the buy-sell imbalances of institutional money managers for stocks sorted on the current day's abnormal trading volume. Overall, these institutional investors exhibit the opposite tendency of the individual investors: Their buy-sell imbalances are greater on low-volume days than high-volume days. This is particularly true for value managers who are aggressive net buyers on days of low abnormal trading volume.

4.2 Returns sorts

Investors are likely to take notice when stocks exhibit extreme price moves. Such returns, whether positive or negative, will often be associated with new information about the firm. Table 2 presents buy-sell imbalances for stocks sorted on the previous day's return. Buy-sell imbalances are reported for

[14] These analyses are available from the authors at http://faculty.haas.berkeley.edu/odean/attention.html.

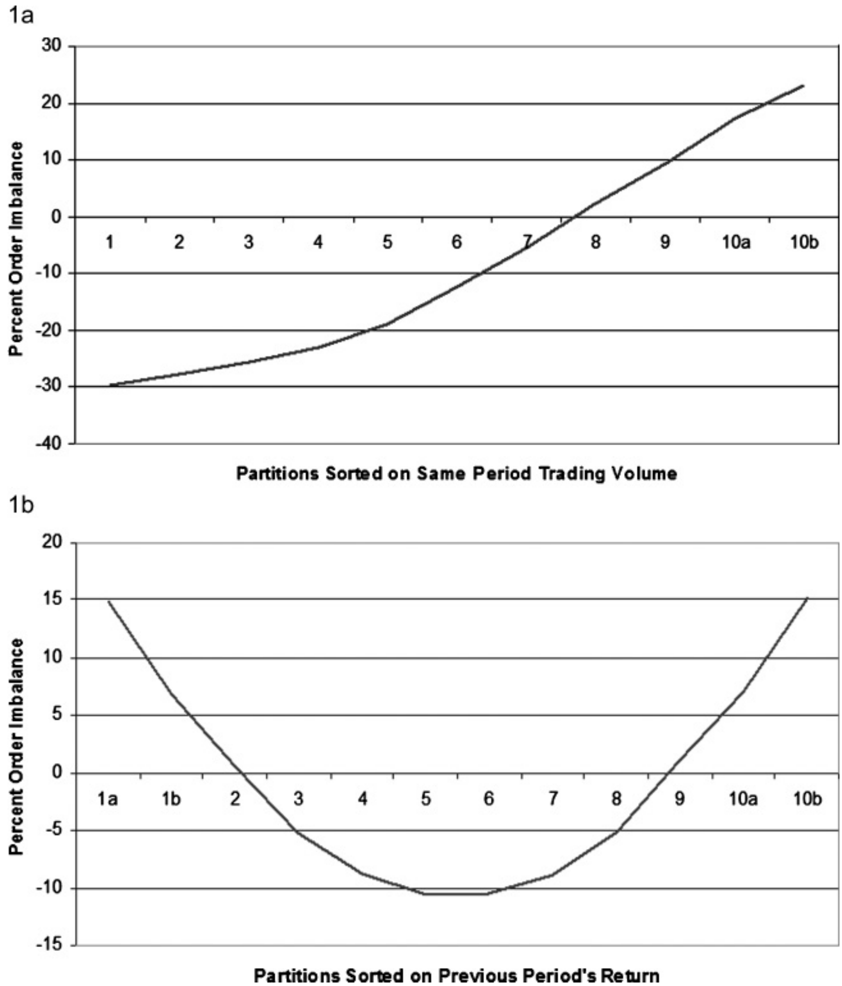

Figure 1
Simulated Buy-Sell Imbalances

We simulate 100,000 realizations of the economy in our model assuming the parameter values $\phi = 2$, $A = 2$, $m = 2$, $\psi = 2$, and $\kappa = 0.5$. Realizations are sorted into partitions on the basis of period 1 return and period 2 trading volume. Buy-sell imbalances are calculated as noise trader buys minus sells divided by noise trader buys plus sells.

investors at a large discount brokerage, a large retail brokerage, a small discount brokerage, and for institutional money managers following momentum, value, and diversified strategies.

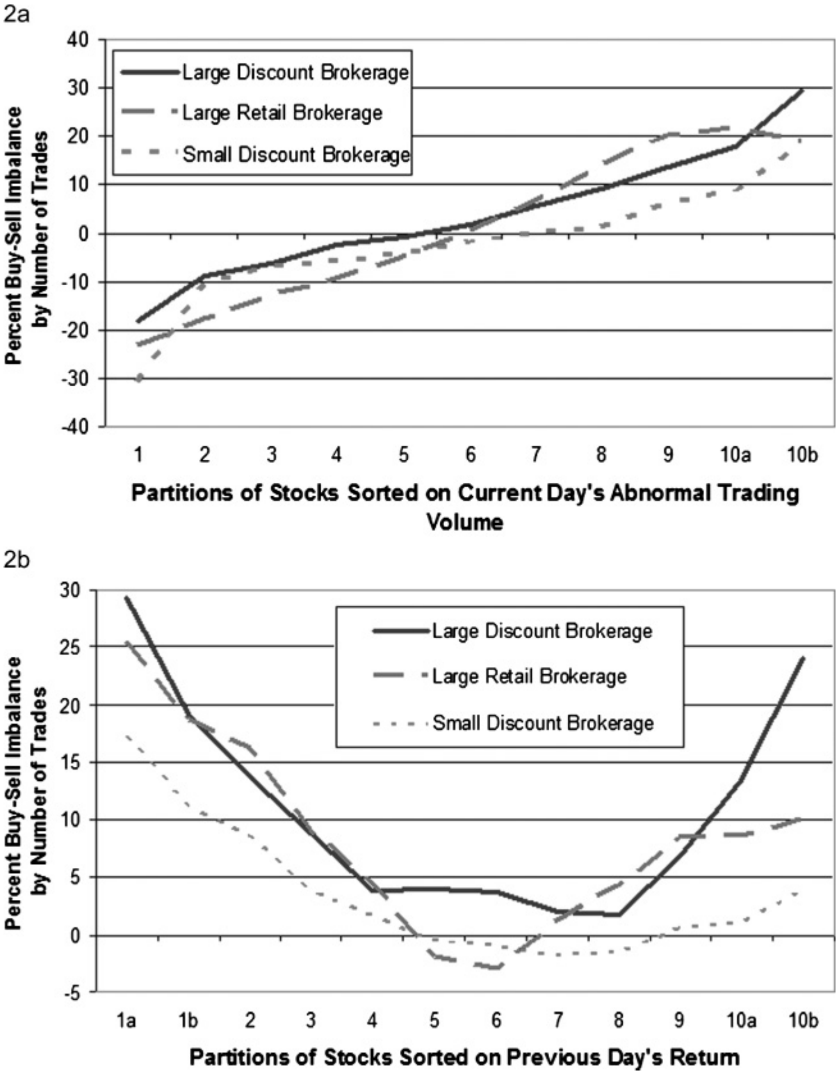

Figure 2
Individual Investor Buy-Sell Imbalances by Number of Trades for Stocks Sorted on the Current Day's Abnormal Trading Volume and Previous Day's Return

Investors at the large discount brokerage display the greatest amount of attention-driven buying for these returns sorts. When calculated by number of trades, the buy-sell imbalance of investors at the large discount brokerage is 29.4% for the vingtile of stocks with the worst return performance on the previous day. The imbalance drops to 1.8% in the eighth return decile and rises back to 24% for stocks with the best return performance on the previous day.

As was the case for abnormal volume, the relation between buy-sell imbalances and returns is quite consistent with the theoretical model (see Appendix). Figure 1b plots average buy-sell imbalances conditional on returns for 100,000 simulations based on our theoretical model. Figure 2b plots buy-sell imbalances based on number of trades for investors at the large discount brokerage, the large retail brokerage, and the small discount brokerage. Note that the simulated and the empirical plots are both U-shaped.[15]

The U-shaped pattern is most pronounced for investors at the large discount brokerage; these investors buy attention-grabbing stocks. When imbalance is calculated by value of trades, the buy-sell imbalance of these investors is 29.1% for the vingtile of stocks with the worst return performance on the previous day. The imbalance drops to −8.6% in the eighth return decile and rises back to 11.1% for stocks with the best return performance on the previous day.

In Figure 2b, we see that investors at the large retail brokerage also display a U-shaped imbalance curve when stocks are sorted on the previous day's return. However, their tendency to be net buyers of yesterday's big winners is more subdued and does not show up when imbalance is calculated by value. Investors at the small discount brokerage are net buyers of yesterday's big losers, but not the big winners.

As seen in the last six columns of Table 2, the three categories of institutional money managers react quite differently to the previous day's return performance. Momentum managers dump the previous day's losers and buy winners. Value managers buy the previous day's losers and dump winners. Diversified managers do this as well, though not to the same extent. Although one might interpret purchases of yesterday's winners by momentum managers and the purchases of yesterday's losers by value managers as attention motivated, it seems more likely that the events leading to extreme positive and negative stock returns coincided with changes relative to the selection criteria that these two groups of money managers follow. Unlike the individual investors, these money managers were not net buyers on high abnormal volume days, nor is any one group of them net buyers following both extreme positive and negative returns.

4.3 News sorts

Table 3 reports average daily buy-sell imbalances for stocks sorted into those with and without news. Investors are much more likely to be net buyers of stocks that are in the news than those that are not. When calculated by number for the large discount brokerage, the buy-sell imbalance is 2.70% for stocks out

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[15] Empirical buy-sell imbalances are very similar when we partition stocks on same-day return rather than on the previous-day return.

Table 2
Buy-sell imbalances by investor type for stocks sorted on the previous day's return

	Large discount brokerage		Large retail brokerage		Small discount brokerage		Momentum managers		Value managers		Diversified managers	
Decile	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance	Number imbalance	Value imbalance
1a (Negative Return)	29.38	29.07	25.79	22.89	17.32	14.90	−21.03	−30.45	17.26	20.09	10.91	18.08
	(0.61)	(0.87)	(1.60)	(1.43)	(1.04)	(1.43)	(1.32)	(1.83)	(3.13)	(3.41)	(2.43)	(2.88)
1b	19.19	16.19	17.86	11.46	11.2	8.58	−6.43	−19.21	14.03	15.62	13.82	15.31
	(0.54)	(0.82)	(1.43)	(1.57)	(1.04)	(1.46)	(1.05)	(1.56)	(2.33)	(2.72)	(1.75)	(2.37)
2	13.69	8.83	13.73	5.47	8.65	3.51	−0.62	−14.58	11.19	11.01	14.18	10.47
	(0.42)	(0.64)	(1.17)	(1.00)	(0.74)	(1.20)	(0.73)	(1.04)	(1.27)	(1.73)	(1.04)	(2.33)
3	8.86	3.11	6.60	−5.01	3.77	1.23	5.10	−3.72	10.23	7.68	12.30	4.75
	(0.45)	(0.63)	(1.18)	(1.09)	(0.76)	(1.23)	(0.71)	(0.96)	(1.06)	(1.44)	(0.92)	(1.29)
4	3.94	−3.28	1.72	−10.98	1.69	−2.75	8.91	4.64	7.98	2.22	11.68	3.04
	(0.45)	(0.64)	(1.06)	(1.07)	(0.84)	(1.31)	(0.76)	(1.00)	(0.99)	(1.34)	(0.90)	(1.26)
5	4.09	−3.57	−4.37	−14.36	−0.6	−3.68	9.84	7.02	9.20	3.69	11.56	2.62
	(0.41)	(0.61)	(0.95)	(0.88)	(0.89)	(1.40)	(0.86)	(1.24)	(1.29)	(1.74)	(1.11)	(1.63)
6	3.73	−4.18	−3.95	−14.98	−0.99	−3.68	11.07	8.97	9.03	3.52	18.12	9.62
	(0.42)	(0.62)	(1.00)	(0.95)	(0.82)	(1.38)	(0.93)	(1.28)	(1.81)	(2.22)	(1.34)	(1.92)
7	2.02	−7.02	−0.07	−15.23	−1.77	−3.29	15.56	16.36	10.61	1.77	15.39	4.18
	(0.44)	(0.64)	(0.91)	(1.12)	(0.82)	(1.28)	(0.75)	(0.99)	(1.18)	(1.55)	(0.96)	(1.36)
8	1.82	−8.62	2.21	−15.85	−1.53	−4.0	19.31	25.22	7.92	0.96	14.00	1.10
	(0.42)	(0.62)	(0.84)	(0.98)	(0.82)	(1.27)	(0.74)	(0.99)	(1.06)	(1.45)	(0.88)	(1.30)
9	6.67	−4.83	6.54	−12.80	0.55	−0.79	22.69	32.44	4.30	−6.06	12.99	−1.70
	(0.43)	(0.62)	(0.88)	(1.08)	(0.73)	(1.13)	(0.69)	(0.93)	(1.21)	(1.66)	(1.02)	(1.55)
10a	13.41	3.23	6.58	−11.24	1.17	−2.93	24.04	34.75	−4.16	−12.66	10.23	−3.98
	(0.51)	(0.78)	(0.90)	(1.17)	(0.96)	(1.41)	(0.93)	(1.37)	(2.14)	(2.57)	(1.58)	(2.24)
10b (Positive Return)	23.98	11.13	9.01	−7.93	3.80	−3.59	21.50	36.37	−17.32	−16.83	7.57	−0.60
	(0.52)	(0.81)	(0.91)	(1.11)	(0.84)	(1.20)	(1.28)	(1.74)	(3.14)	(3.41)	(2.30)	(2.81)

Stocks are sorted daily into deciles on the basis of the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a, and 10b). Buy-sell imbalances are reported for the trades of six groups of investors, investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through 15 June 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey–West correction for serial dependence, appear in parentheses.

of the news and 9.35% for those in the news. At the large retail brokerage, the buy-sell imbalance is −1.84% for stocks out of the news and 16.17% for those in the news.

Table 3 also reports news partition buy-sell imbalances separately for days on which individual stocks had a positive, negative, or zero return. Conditional on the sign of the return, average imbalances for individual investors are always greater on news days than no-news days. For both news and no-news days, average imbalances are greater for negative return days than for positive return days. One possible explanation for this is that when stock prices drop, investors are less likely to sell due to the disposition effect—i.e., the preference for selling winners and holding losers. Alternatively, the differences in imbalances on positive and negative return days may result from the execution of limit orders. Many individual investors will not monitor their limit orders throughout the day. On a day when the market rises, more sell limit orders will execute than buy limit orders. On days when the market falls, more buy limit orders will execute. Unfortunately, our datasets do not distinguish between executed limit and market orders.

4.4 Volume, return, and news sorts

We examine the possibility of interaction effects in our measures of attention by analyzing buy-sell imbalances for stocks partitioned on abnormal trading volume, previous day's return, and whether or not a stock had news coverage. Abnormal volume and previous day's returns are independently sorted into three bins—bottom 30%, middle 40%, and top 30%. The three-by-three partition on volume and returns is further conditioned on whether a stock was in the news. Order imbalances are calculated based on number of trades. The results of this analysis are presented in Figure 3. Consistent with the univariate sorts, buy-sell imbalances increase with abnormal volume for each return partition. At the large discount brokerage, for each volume partition, buy-sell imbalances are the greatest for the low and high return bins. At the large retail brokerage, for each volume partition, buy-sell imbalances are consistently greater for low return bins, and for high return bins with no news or low volume. At the small discount brokerage, for each volume partition, buy-sell imbalances are consistently greater for low return bins, but there is no consistent effect for high return bins. Finally, buy-sell imbalances tend to be greater for the news partition, for high- and low-volume stocks at the large discount brokerage, for high- and medium-volume stocks at the large retail brokerage, and for high-volume stocks at the small discount brokerage. It appears from this analysis and from our univariate tests that abnormal trading volume is our single best indicator of attention. Returns come in second. Our simple news metric—whether a stock was or was not mentioned in that day's news—is our least informative indicator of attention. It is hardly surprising that abnormal volume best measures attention, since greater trading volume is often driven by greater numbers of

Table 3
Buy-Sell Imbalances by Investor Type for Stocks Sorted on the Current Day's News

Partition	Large discount brokerage Number imbalance	Large discount brokerage Value imbalance	Large retail brokerage Number imbalance	Large retail brokerage Value imbalance	Small discount brokerage Number imbalance	Small discount brokerage Value imbalance	Momentum managers Number imbalance	Momentum managers Value imbalance	Value managers Number imbalance	Value managers Value imbalance	Diversified managers Number imbalance	Diversified managers Value imbalance
Panel A: All Days												
News	9.35	0.07	16.17	−2.36	6.76	1.87	13.38	14.00	6.36	−0.24	6.21	2.26
	(0.72)	(0.86)	(1.29)	(1.32)	(0.48)	(0.72)	(1.33)	(1.71)	(1.59)	(2.05)	(1.11)	(1.50)
No News	2.70	−5.62	−1.84	−14.59	−0.66	−4.87	12.20	10.43	10.96	3.62	7.26	1.24
	(0.43)	(0.63)	(0.87)	(0.87)	(0.58)	(1.23)	(1.11)	(1.16)	(1.37)	(1.49)	(0.97)	(0.84)
Panel B: Positive Return Days												
News	1.74	−9.25	14.07	−7.74	1.14	−3.13	22.70	31.95	5.87	−1.01	7.80	3.92
	(0.94)	(1.07)	(1.04)	(1.25)	(0.64)	(0.95)	(1.50)	(2.10)	(1.94)	(2.65)	(1.31)	(2.00)
No News	−2.51	−14.31	1.76	−13.90	−4.49	−8.41	22.39	25.64	14.20	6.67	8.95	6.66
	(0.54)	(0.79)	(0.88)	(1.00)	(0.79)	(1.40)	(1.31)	(1.46)	(1.51)	(1.74)	(1.05)	(1.05)
Panel C: Negative Return Days												
News	17.39	10.91	15.59	3.17	13.77	9.32	3.94	−7.39	4.29	−2.41	4.72	2.24
	(0.83)	(1.12)	(1.58)	(1.43)	(0.71)	(1.08)	(1.43)	(2.11)	(2.09)	(2.77)	(1.30)	(2.25)
No News	8.86	3.85	−3.38	−13.57	4.35	1.29	0.68	−8.60	6.92	1.60	5.58	−4.11
	(0.53)	(0.81)	(0.88)	(0.85)	(0.77)	(1.42)	(1.25)	(1.46)	(1.52)	(1.89)	(1.03)	(1.23)
Panel C: Zero Return Days												
News	1.41	−5.90	−0.44	−8.74	1.58	−1.22	14.12	15.16	11.37	9.59	5.21	1.62
	(1.76)	(2.31)	(0.94)	(1.45)	(2.25)	(2.68)	(2.35)	(3.19)	(3.44)	(4.35)	(2.47)	(3.68)
No News	−0.95	−6.40	−14.49	−18.24	−3.27	−7.95	14.60	12.86	10.65	2.42	8.36	−0.17
	(0.68)	(1.13)	(1.06)	(1.08)	(1.35)	(2.04)	(1.38)	(1.81)	(1.73)	(2.49)	(1.27)	(1.84)

Stocks are partitioned daily into those with and without news stories (reported by the Dow Jones News Service) that day. On average, there is no news for 91% of stocks. Buy-sell imbalances are reported for the trades of six groups of investors, investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), investors at a small discount brokerage (January 1996 through 15 June 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. Buy-sell imbalances are reported for all stocks and days with or without news. They are also reported separately for the days on which stocks had positive, negative, and zero returns. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

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traders, and it is nearly tautological that when more people are trading a stock, more people are paying attention to it.

4.5 Size partitions

To test whether our results are driven primarily by small capitalization stocks, we calculate buy-sell imbalances separately for small, medium, and large capitalization stocks. We first sort and partition all stocks as described above on the basis of same-day abnormal trading volume, the previous-day return, and same-day news. We then calculate imbalances separately for small, medium, and large capitalization stocks using the same breakpoints to form abnormal volume and return deciles for all the three size groups. We use monthly New York Stock Exchange market equity breakpoints to form our size groups.[16] Each month, we classify all stocks (both NYSE-listed and nonlisted stocks) with market capitalization less than or equal to the thirtieth percentile breakpoint as small stocks, stocks with market capitalization greater than the thirtieth percentile and less than or equal to the seventieth percentile as medium stocks, and stocks with market capitalization greater than the seventieth percentile as large stocks. Table 4 reports buy-sell imbalances by size group for abnormal volume, return, and news sorts.[17]

By and large, investors are more likely to buy rather than sell attention-grabbing stocks regardless of size. This is true for all three of our attention-grabbing measures: abnormal trading volume, returns, and news. Many documented return anomalies, such as momentum and postearning announcement drift, are greater for small capitalization stocks than for large stocks. Some researchers have suggested that these phenomena may be caused by the psychologically motivated trading behavior of individual investors. We find, however, that attention-driven buying by individuals is as strong for large capitalization stocks as for small stocks. It may be that while the impact of individual investor trading differs for large and small stocks, the psychological biases motivating trading are the same.[18]

4.6 Earnings and dividend announcements

To test the robustness of our results, we calculate buy-sell imbalances for abnormal volume partitions, return partitions, and news and no-news for earnings announcement days, dividend announcement days, and other days. Earnings

[16] We thank Ken French for supplying market equity breakpoints. These breakpoints are available and further described in Ken French's online data library.

[17] To save space, results are reported only for the investors most likely to display attention-driven buying—those at the large discount brokerage. Results for the large retail and small discount brokerages are qualitatively similar. The only significant exception to this pattern is that buy-sell imbalances at the large retail brokerage for large capitalization stocks are no greater for deciles of high previous-day returns than for the middle return deciles. For small cap and medium cap stocks, these retail investors do demonstrate a greater propensity to buy yesterday's winners than yesterday's average performers.

[18] Institutional buy-sell imbalance for our volume and return sorts is also qualitatively similar across small, medium, and large firms.

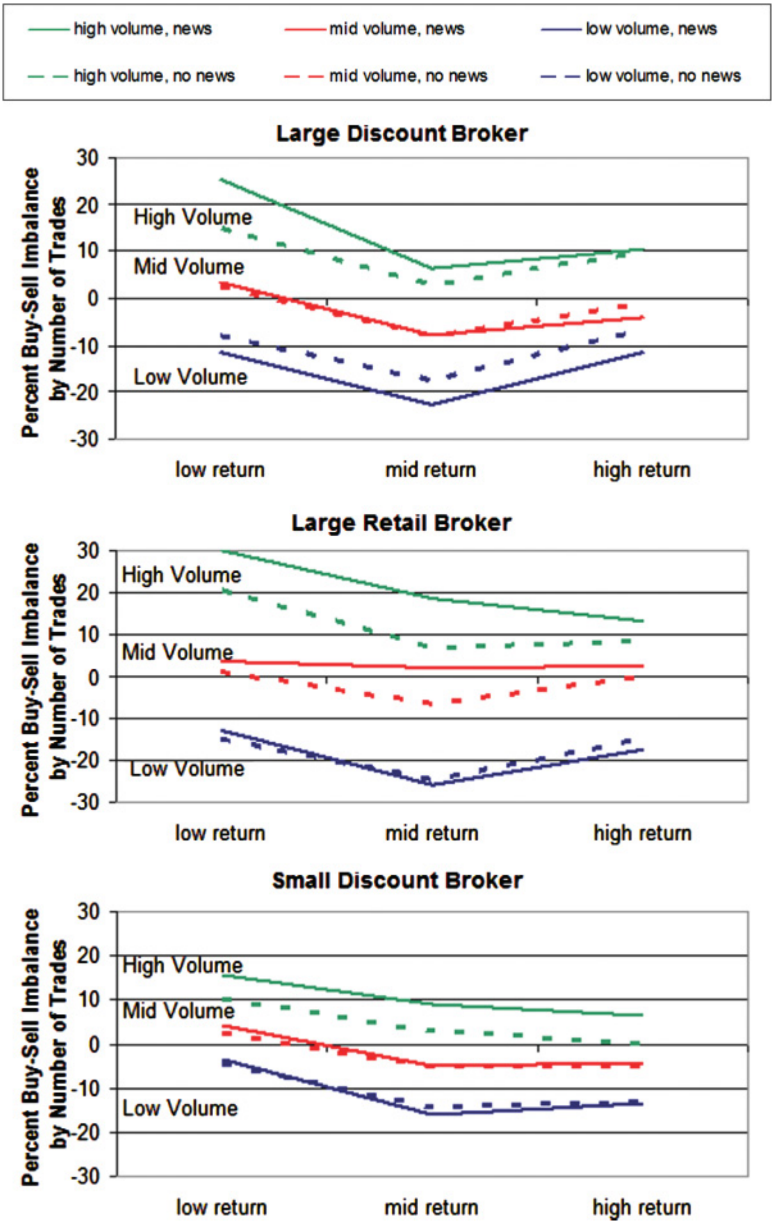

Figure 3
Buy-Sell Imbalances for Investors at a Large Discount Brokerage Based on 3-by-3 Partition on Abnormal Volume and Returns, Conditional on News Coverage

Table 4
Buy-Sell Imbalances for Large Discount Brokerage Investors for Stocks Sorted on the Current Day's Abnormal Trading Volume, the Previous Day's Return, and the Current Day's News and Then Partitioned on Market Capitalization
Panel A: Buy-Sell Imbalances for Stocks Sorted First on Current Day's Abnormal Trading Volume and Then on Market Capitalization

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	−16.11	−13.35	−18.43	−17.18	−31.89	−30.33
	(1.17)	(1.50)	(2.36)	(2.49)	(6.32)	(6.46)
2	−5.94	−4.37	−12.09	−14.16	−21.44	−22.17
	(0.86)	(1.18)	(1.19)	(1.50)	(2.32)	(2.49)
3	−2.23	−2.49	−6.66	−9.24	−15.81	−15.35
	(0.72)	(1.04)	(0.85)	(1.19)	(1.29)	(1.56)
4	3.22	0.16	−1.99	−6.65	−9.17	−13.01
	(0.71)	(1.01)	(0.70)	(1.05)	(0.76)	(1.11)
5	6.22	2.96	1.54	−4.30	−5.46	−9.99
	(0.70)	(1.01)	(0.67)	(1.01)	(0.58)	(0.87)
6	9.44	5.74	2.94	−5.00	−1.24	−9.12
	(0.65)	(0.96)	(0.62)	(0.95)	(0.54)	(0.77)
7	10.90	4.47	6.03	−0.99	4.02	−3.27
	(0.64)	(0.97)	(0.59)	(0.92)	(0.54)	(0.76)
8	11.83	5.42	6.80	−1.88	9.38	−0.80
	(0.61)	(0.92)	(0.57)	(0.89)	(0.56)	(0.77)
9	15.13	7.27	9.27	−0.98	14.50	4.54
	(0.53)	(0.83)	(0.59)	(0.85)	(0.64)	(0.84)
10a	16.94	7.73	12.97	3.80	19.76	11.13
	(0.64)	(0.99)	(0.76)	(1.05)	(0.99)	(1.22)
10b (highest volume)	20.77	32.13	24.41	15.04	28.26	21.65
	(0.54)	(0.83)	(0.86)	(1.12)	(1.33)	(1.53)

In panel A, stocks are sorted daily into deciles on the basis on the current day's abnormal volume. The decile of highest abnormal volume is split into two vingtiles (10a and 10b). Abnormal volume is calculated as the ratio of the current day's volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average volume over the previous 252 trading days. In Panel B, stocks are sorted daily into deciles on the basis of the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In Panel C, stocks are partitioned daily into those with and without news stories that day (as reported by the Dow Jones News Service). On average there is no news for 91 percent of stocks. For all three panels, after sorting and partitioning, stocks are further separated into three groups based on market capitalization. We use monthly New York Stock Exchange market equity breakpoints to form our size groups. Each month we classify all stocks (both NYSE-listed and non-listed stocks) with market capitalization less than or equal to the thirtieth percentile breakpoint as small stocks, stocks with market capitalization greater than thirtieth percentile and less than or equal to the seventieth percentile as medium stocks, and stocks with market capitalization greater than the seventieth percentile as large stocks. Buy-sell imbalances are reported for the trades of investors at a large discount brokerage (January 1991 through November 1996). For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

announcement days span day $t-1$ to $t+2$, where day t is the earnings announcement day (per Compustat). Dividend announcement days span day $t-1$ to $t+2$, where day t is the dividend announcement day (per CRSP). We include all dividend announcements regardless of type. As seen in Figure 4, for volume,

Table 4
Panel B: Buy-Sell Imbalances for Stocks Sorted First on the Previous Day's Return and Then on Market Capitalization

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	24.88	26.06	32.71	30.83	38.73	34.55
	(0.66)	(0.99)	(1.25)	(1.48)	(1.92)	(2.15)
1b	14.37	12.61	17.61	14.99	25.26	21.93
	(0.65)	(0.99)	(0.96)	(1.27)	(1.38)	(1.62)
2	10.69	6.30	9.67	4.99	18.53	13.50
	(0.54)	(0.82)	(0.06)	(0.89)	(0.67)	(0.92)
3	6.97	2.05	5.06	−0.95	11.09	5.35
	(0.65)	(0.96)	(0.59)	(0.86)	(0.59)	(0.82)
4	4.48	−3.23	0.87	−5.29	4.23	−3.06
	(0.53)	(0.78)	(0.62)	(0.90)	(0.60)	(0.81)
5	3.72	−3.64	3.59	−4.45	4.02	−3.58
	(0.42)	(0.63)	(0.46)	(0.69)	(0.47)	(0.67)
6	4.20	−3.64	4.46	−3.07	2.86	−4.96
	(0.42)	(0.62)	(0.49)	(0.73)	(0.54)	(0.75)
7	5.28	−2.63	2.87	−4.84	0.80	−8.23
	(0.54)	(0.79)	(0.60)	(0.90)	(0.59)	(0.81)
8	8.88	2.78	2.07	−7.78	−0.83	−10.96
	(0.61)	(0.93)	(0.56)	(0.85)	(0.58)	(0.80)
9	11.98	5.49	6.73	−5.41	3.31	−6.69
	(0.54)	(0.83)	(0.61)	(0.90)	(0.67)	(0.90)
10a	16.88	10.59	12.09	2.53	5.53	−1.81
	(0.63)	(0.96)	(0.82)	(1.14)	(1.25)	(1.48)
10b (Positive Return)	26.98	18.69	20.85	8.19	7.76	2.94
	(0.57)	(0.88)	(1.06)	(1.33)	(1.84)	(2.06)

Table 4
Panel C: Buy-Sell Imbalances for Stocks Sorted First on Market Capitalization and Then on Current Day's News

	Small Stocks		Mid Cap Stocks		Large Stocks	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
News	19.87	14.59	13.38	3.87	6.52	−1.35
All Days	(1.47)	(1.85)	(1.15)	(1.62)	(0.85)	(0.97)
No News	7.53	2.82	3.12	−4.83	−2.91	−9.86
All Days	(0.48)	(0.70)	(0.57)	(0.88)	(0.67)	(0.94)

return, and news sorts, the buy-sell imbalance results are qualitatively similar across the three partitions.[19]

5. Short-Sale Constraints

We argue that because individual investors hold small portfolios and do not sell short, attention is more important when choosing stocks to buy—from a huge set of choices—than when choosing stocks to sell—from a small set. Short-

[19] To save space, results are reported only for the investors most likely to display attention-driven buying—those at the large discount brokerage. Results for the large retail and small discount brokerages are qualitatively similar and available from the authors.

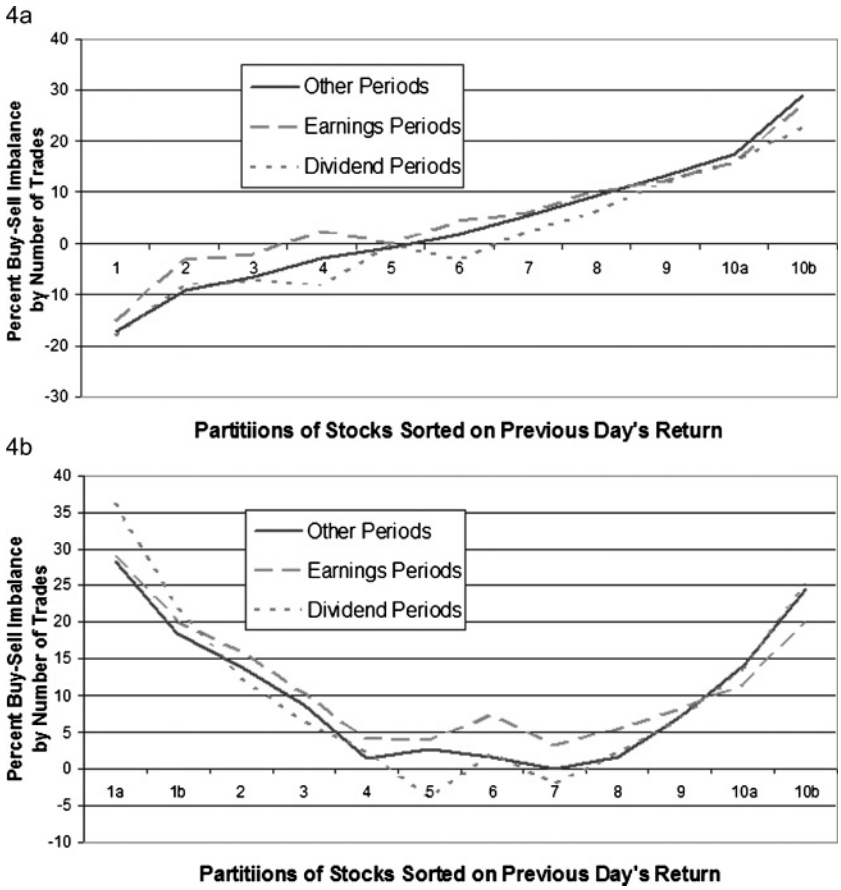

Figure 4
Buy-Sell Imbalances for Investors at a Large Discount Brokerage During Earnings Announcement Periods, Dividend Announcement Periods, and Other Periods, for Volume Deciles (top) and Return Deciles (bottom)

sale constraints could contribute to our empirical findings through a somewhat different mechanism. An attention-grabbing event may increase heterogeneity of investor beliefs about a firm. Individual investors who become bullish are able to buy the stock, but those who become bearish can sell it only if they already own it or are willing to sell short. Institutional investors can both buy and sell. Thus, on average, bullish individuals and institutions buy attention-grabbing stocks while bearish institutions, but not individuals, sell. Attention-grabbing events are therefore associated with net buying by individuals, not because individuals are buying what catches their attention, but because they can't sell what catches their attention; attention-grabbing events increase heterogeneity of beliefs, while limited portfolios and short-sale constraints restrict would-be sellers.

We believe that increased heterogeneity of beliefs combined with selling constraints may contribute to net buying by individuals around attention-grabbing events. However, even when individuals have the option both to buy and to sell a stock—i.e., when they already own the stock—attention will matter more for buying. If short-sale constraints alone mattered and attention did not otherwise differentially affect buying and selling, we would expect attention-grabbing events to exert a similar influence on both the sales and the purchases of stocks that investors already own. The attention hypothesis makes a different prediction. The attention hypothesis states that attention is important when investors face a search problem. Each potential purchase—even of a stock already in the portfolio—is competing with thousands of other stocks for attention. Thus, attention affects the rate at which stocks are purchased, even stocks that are already owned. Of course investors are, overall, more likely to sell than buy stocks they already own. Under the attention hypothesis, however, the buy-sell imbalances of stocks that investors already own should be greater on days in which those stocks are attention-grabbing.

In Table 5, we report buy-sell imbalances for individual investors for abnormal volume, return, and news sorts for stocks. In calculating imbalances for this table, we consider only purchases and sales by each investor of stocks he or she already owns. Since investors mostly sell stocks that they already own, but often buy stocks that they do not own, a far greater proportion of these trades are sales. Therefore, nearly all of the imbalances are negative. The relative patterns of imbalances are, however, similar to those reported for individual investors in Tables 1, 2, and 3. The ratio of purchases to sales is higher on high-attention days. This is particularly true for the abnormal volume sort (Panel A) and the news sort (Panel C). When stocks are sorted on the previous day's return (Panel B), investors are relatively more likely to purchase stocks they already own on days following large negative returns than on other days. However, following large positive returns, buy-sell imbalances do not increase for stocks already owned. This is consistent with previous research (Odean, 1998a) that finds that individual investors are more likely to sell stocks trading above, rather than below, the original purchase price and more likely to buy additional shares of stocks trading below, rather than above, the original purchase price.

Short-sale constraints are relaxed in the presence of exchange-traded options. Thus, if short-sale constraints alone drive our results, we would expect much different results for stocks with exchange-traded options. In auxiliary analyses, we partition stocks into two groups—those with and those without exchange-traded options.[20] For each group, we sort stocks into deciles on the basis of abnormal trading volume and previous day's return and calculate buy-sell imbalances for each decile (as described in Section 3). The patterns of imbalances

[20] We thank Charles Cao for providing us with a list of stocks with exchange-traded options.

Table 5
Buy-sell imbalances for large discount brokerage investors for stocks already owned by each investor. stocks sorted on the current day's abnormal trading volume, the previous day's return, and the current day's news
Panel A: Buy-Sell Imbalances for Stocks Already Owned Sorted on Current Day's Abnormal Trading Volume

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	−54.22 (1.43)	−55.64 (1.89)	−28.74 (1.42)	−33.99 (1.84)	−24.25 (6.28)	−33.22 (7.58)
2	−51.13 (0.78)	−53.20 (1.07)	−29.46 (1.09)	−34.09 (1.36)	−33.80 (3.18)	−29.67 (4.47)
3	−48.27 (0.64)	−49.69 (0.95)	−29.54 (1.04)	−31.25 (1.31)	−31.76 (1.71)	−30.05 (2.44)
4	−47.19 (0.56)	−49.51 (0.88)	−28.69 (0.94)	−32.96 (1.11)	−35.65 (1.26)	−33.93 (1.96)
5	−45.95 (0.53)	−47.59 (0.81)	−26.71 (0.90)	−31.04 (1.07)	−32.34 (1.12)	−30.01 (1.63)
6	−45.01 (0.49)	−48.65 (0.71)	−24.32 (0.90)	−29.71 (1.04)	−30.00 (0.97)	−26.50 (1.42)
7	−42.36 (0.50)	−45.85 (0.71)	−21.83 (0.84)	−30.29 (0.89)	−29.85 (0.95)	−26.21 (1.33)
8	−39.43 (0.51)	−43.75 (0.71)	−18.72 (0.81)	−27.21 (0.87)	−28.20 (0.87)	−26.23 (1.22)
9	−35.64 (0.52)	−40.68 (0.70)	−15.45 (0.78)	−21.79 (0.91)	−27.07 (0.85)	−24.99 (1.21)
10a	−33.03 (0.63)	−39.31 (0.85)	−12.27 (0.97)	−19.97 (1.12)	−26.81 (1.06)	−27.99 (1.42)
10b (highest volume)	−24.97 (0.69)	−32.82 (0.92)	−15.01 (1.04)	−20.04 (1.19)	−17.32 (0.98)	−19.38 (1.42)

In panel A, stocks are sorted daily into deciles on the basis of the current day's abnormal volume. The decile of the highest abnormal volume is split into two vingtiles (10a and 10b). Abnormal volume is calculated as the ratio of the current day's volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average volume over the previous 252 trading days. In panel B, stocks are sorted daily into deciles on the basis of the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. The deciles of highest and lowest returns are each split into two vingtiles (1a, 1b, 10a, and 10b). Abnormal trading volume is calculated as the ratio of the current day's trading volume (as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks) divided by the average trading volume over the previous 252 trading days. In panel C, stocks are partitioned daily into those with and without news stories that day (as reported by the Dow Jones News Service). Buy-sell imbalances are reported for the trades of investors at a large discount brokerage (January 1991 through November 1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount brokerage (January 1996 through December 1998). Imbalances are calculated for purchases and sales by investors of stocks already held by each investor's account. For each day/partition/investor group, we calculate number imbalance as number of purchases minus number of sales divided by total number of trades. Value imbalance is calculated as the value of purchases minus the value of sales divided by the total value of trades. The table reports the mean for each time series of daily imbalances for a particular investor group and partition. Standard errors, calculated using a Newey-West correction for serial dependence, appear in parentheses.

are very similar for stocks with and without exchange-traded options—another indication that the results we document are not driven by short-sale constraints.

Thus, short-selling constraints (and heterogeneity of beliefs) do not fully explain our findings. For individual investors who can sell a stock without selling short, a higher percentage of their trades consists of purchases, rather than sales, on high-attention days.

Table 5
Panel B: Buy-Sell Imbalances for Stocks Already Owned Sorted on the Previous Day's Return

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1a (Negative Return)	−9.68	−11.96	4.05	0.33	−16.89	−19.68
	(0.83)	(1.17)	(0.99)	(1.26)	(1.54)	(1.85)
1b	−23.90	−26.00	−8.20	−10.83	−18.90	−21.86
	(0.76)	(1.02)	(0.99)	(1.20)	(1.49)	(1.84)
2	−32.00	−33.15	−12.73	−14.99	−22.71	−24.77
	(0.56)	(0.76)	(0.89)	(1.00)	(1.09)	(1.45)
3	−38.94	−40.22	−18.24	−21.85	−27.10	−26.23
	(0.57)	(0.76)	(0.94)	(0.99)	(1.16)	(1.53)
4	−42.53	−44.79	−20.36	−25.16	−26.03	−26.47
	(0.56)	(0.78)	(0.91)	(1.01)	(1.24)	(1.58)
5	−40.51	−44.29	−20.67	−24.83	−27.67	−27.77
	(0.55)	(0.76)	(0.93)	(1.10)	(1.46)	(1.75)
6	−41.18	−45.31	−21.35	−26.59	−28.54	−27.29
	(0.55)	(0.77)	(0.90)	(1.10)	(1.42)	(1.73)
7	−45.36	−49.57	−22.82	−28.66	−29.28	−28.44
	(0.57)	(0.78)	(0.89)	(1.06)	(1.24)	(1.55)
8	−48.12	−52.42	−25.45	−32.00	−31.14	−28.16
	(0.50)	(0.70)	(0.87)	(1.02)	(1.24)	(1.61)
9	−45.85	−50.13	−27.13	−34.00	−32.70	−28.40
	(0.49)	(0.68)	(0.79)	(0.95)	(1.09)	(1.45)
10a	−40.86	−46.06	−31.17	−38.16	−36.03	−34.85
	(0.64)	(0.89)	(0.85)	(1.03)	(1.27)	(1.67)
10b (Positive Return)	−33.95	−43.77	−29.73	−34.87	−35.02	−38.31
	(0.68)	(0.94)	(0.81)	(1.05)	(1.20)	(1.49)

Table 5
Panel C: Buy-Sell Imbalances for Stocks Already Owned Sorted on Current Day's News

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
News	−40.91	−42.36	−15.38	−23.95	−22.14	−22.02
All Days	(0.79)	(0.94)	(0.94)	(0.98)	(0.91)	(1.52)
No News	−45.05	−45.98	−21.42	−25.46	−32.77	−33.68
All Days	(0.52)	(0.77)	(0.92)	(1.02)	(1.00)	(1.52)

6. Conclusion

We propose model of decision making in which agents faced with many alternatives consider primarily those alternatives that have attention-attracting qualities. Preferences come into play only after attention has limited the choice set. When alternatives are many and search costs high, attention may affect choice more profoundly than preferences do. If the attention-grabbing characteristics of an alternative coincide with the characteristics that increase utility, agents may benefit from the role of attention in reducing search costs. However, if attention and utility are orthogonal or negatively correlated, expected utility may be diminished. Under some circumstances, the utility of an alternative is affected by how many agents choose that alternative. Thus, the attention-attracting qualities of an alternative may indirectly detract from its utility. For example, a well-circulated article about a deserted vacation spot could attract the attention and the travel plans of many vacationers, each of whom would be disappointed by the crowds of like-minded tourists. Similarly, attention-based purchases by many investors could temporarily inflate a stock's price, leading to disappointing subsequent returns.

Attention-based decision making has implications for a wide variety of economic situations (for example, hiring decisions or consumer purchases). In this paper, we test this model of decision making in the context of common stock purchases. Choosing which common stock to buy presents investors with a huge search problem. There are thousands of possibilities. When selling, most investors consider only stocks they already own, which are typically few in number and can be considered one by one. When buying, however, it is impossible—without the aid of a computer—for most investors to evaluate the merits of every available common stock.

We argue that many investors solve this search problem by considering for purchase only those stocks that have recently caught their attention. While they do not buy every stock that catches their attention, they buy far fewer that do not. Within the subset of stocks that do attract their attention, investors are likely to have personal preferences—contrarians, for example, may select stocks that are out of favor with others. But whether a contrarian or a trend follower, an investor is less likely to purchase a stock that is out of the limelight.

Professional investors are less prone to indulge in attention-driven purchases. With more time and resources, professionals are able to monitor continuously a wider range of stocks. They are unlikely to consider only attention-grabbing stocks. Professionals are likely to employ explicit purchase criteria—perhaps implemented with computer algorithms—that circumvent attention-driven buying. Furthermore, many professionals may solve the problem of searching through too many stocks by concentrating on a particular sector or on stocks that have passed an initial screen.

We test for attention-driven buying by sorting stocks on events that are likely to coincide with catching investors' attention. We sort on abnormal trading volume, since heavily traded stocks must be attracting investors' attention. We sort on extreme one-day returns since—whether good or bad—these are likely to coincide with attention-grabbing events. And we sort on whether or not a firm is in the news.

Consistent with our predictions, we find that individual investors display attention-driven buying behavior. They are net buyers on high-volume days, following both extremely negative and extremely positive one-day returns, and when stocks are in the news. Attention-driven buying is similar for large capitalization stocks and for small stocks. The institutional investors in our sample—especially the value-strategy investors—do not display attention-driven buying.

Previous work has shown that most investors do not benefit from active trading. On average, the stocks they buy subsequently underperform those they sell (Odean, 1999), and the most active traders underperform those who trade less (Barber and Odean, 2000). The attention-driven buying patterns we document here do not generate superior returns. We believe that most investors will benefit from a strategy of buying and holding a well-diversified portfolio. Investors who insist on hunting for the next brilliant stock would be well advised to remember what California prospectors discovered ages ago: All that glitters is not gold.

Appendix: The Model

Attention-driven noise traders and a risk-neutral, privately informed insider submit market orders to a risk-neutral market-maker as in Kyle (1985). There are four periods with two rounds of trading. The economy has two assets, a riskless asset and a risky asset. The riskless interest rate is assumed to be 0. The distributions of all market parameters are known to the insider and to the market-maker. The terminal value of the risky asset is $\tilde{v} = \tilde{y}_1 + \tilde{y}_2$, $\tilde{y}_t \sim N\left(0, \phi^2\right)$ for $t = 1, 2$. $\tilde{y}_1$ and $\tilde{y}_2$ are independent and can be thought of as the firm's period 1 and 2 earnings. Prior to trading at times $t = 1, 2$, the risk-neutral insider observes$\tilde{y}_t$. After observing $\tilde{y}_t$, the insider demands (submits a market order for) x_t units of the risky asset; $x_t < 0$ is interpreted to be a sell order. $\tilde{y}_t$is publicly revealed to the noise traders and to the market-maker at time t+1, that is, one period after it is observed by the insider. Thus, at $t = 2$, $\tilde{y}_1$ is common knowledge. The revelation of $\tilde{y}_1$ proxies for news in the model. We assume that at $t = 2$, the level of attention paid to the risky asset by attention-driven noise traders is proportional to $\tilde{y}_1^2$.

Without regard to price or value, noise traders submit market orders to buy $\tilde{b}_t \sim \mathrm{N}\left(E\left(\tilde{b}_t\right), \sigma_{bt}^2\right)$ units and to sell $\tilde{s}_t \sim \mathrm{N}\left(E\left(\tilde{s}_t\right), \sigma_{st}^2\right)$ units of the risky asset. In period 2, noise trader buying depends upon the attention generated by news,$\tilde{y}_1$. But, just as in actual markets, not all noise trader activity depends on attention. We set $E\left(\tilde{b}_2|\tilde{y}_1\right) = m\left(A + \tilde{y}_1^2\right)$, where $m > 0$ is a measure of the intensity of noise trading, $m\tilde{y}_1^2$ is the expected level of attention-driven buying, and $mA > 0$ is the expected level of non–attention-driven noise trader buying. Setting attention-driven buying in period 2 as proportional to$\tilde{y}_1^2$ captures our assumption that attention-based traders will be net buyers on good news (i.e., $\tilde{y}_1 > 0$) or bad news (i.e., $\tilde{y}_1 < 0$) and is consistent with the observation that news tends to focus more intensely on extreme events, and is consistent with the empirical results reported in Section 4.2. Our contention is that attention has a greater effect on buying than on selling. So we set $E\left(\tilde{s}_2|\tilde{y}_1\right) = m\left(A + \kappa\tilde{y}_1^2 + (1-\kappa)\phi^2\right)$, where κ, $0 \leqslant \kappa < 1$, determines how much attention affects selling compared to buying. Note that the unconditional expectations of $\tilde{b}_2$ and $\tilde{s}_2$ are equal—i.e.,$E\left(\tilde{b}_2\right) = E\left(\tilde{s}_2\right) = m\left(A + \phi^2\right)$; therefore, unconditional net buying (buys minus sells) equals zero. For consistency we also set $E\left(\tilde{b}_1\right) = E\left(\tilde{s}_1\right) = m\left(A + \phi^2\right)$. Finally, the variances of noise trader buying and selling are assumed to be proportional to the means—that is, $\sigma_{b1}^2 = E\left(\tilde{b}_1\right)/\psi^2$, $\sigma_{s1}^2 = E(\tilde{s}_1)/\psi^2$, $\sigma_{b2}^2 = E\left(\tilde{b}_2|\tilde{y}_1^2\right)/\psi^2$, and $\sigma_{s2}^2 = E\left(\tilde{s}_2|\tilde{y}_1^2\right)/\psi^2$, where $\psi > 0$ is a scaling factor.[21] P_0, the period 0 price of the risky asset, is assumed to equal its unconditional expected terminal value, $\bar{v} = 0$, andP_3, the period 3 price, is set equal to the realized terminal value of the risky asset, which is public knowledge in period 3—that is, $P_3 = \tilde{v} = \tilde{y}_1 + \tilde{y}_2$. We are primarily interested in trading at $t = 2$, when the trading activity of noise traders is influenced by the attention associated with the public revelation of the insider's first period signal,$\tilde{y}_1$.

The insider conjectures that the market-maker's price-setting function is a linear function of total demand $d_t = x_t + \tilde{b}_t - \tilde{s}_t$,

[21] In unreported analyses, we confirm that for all three of our attention sort criteria and for investors at all three brokerages, the variance of purchases tends to be greater on days that stocks are sorted in high attention partitions.

$$P_t = \mu + \lambda d_t. \tag{4}$$

He chooses x_t to maximize his expected trading profits, $x_t\,(\tilde{v} - P_t)$, conditional on his signal, $\tilde{y}_t$, and the conjectured price function.[22] We assume, as in Kyle (1985), that due to perfect competition, the market-maker earns zero expected profits. The market-maker conjectures that the insider's demand function is a linear function of $\tilde{y}_t$,

$$x_t = \alpha + \beta \tilde{y}_t. \tag{5}$$

She sets price to be the expected value of $\tilde{v}$ conditional on total demand, d_t, given the conjectured demand function.

Lemma 1. *An equilibrium exists in which the insider's linear price conjecture, Equation (4), and the market-maker's linear demand conjecture, Equation (5), are fulfilled. In equilibrium, the coefficients of Equations (4) and (5) for period $t=2$ are*

$$\alpha = 0 \tag{6}$$

$$\beta = \frac{1}{\psi\phi}\sqrt{m\left(2A + (1+\kappa)\tilde{y}_1^2 + (1-\kappa)\phi^2\right)} \tag{7}$$

$$\mu = \tilde{y}_1 - \frac{\psi\phi\left(E\left(\tilde{b}_2|\tilde{y}_1^2\right) - E\left(\tilde{s}_2|\tilde{y}_1^2\right)\right)}{2\sqrt{m\left(2A + (1+\kappa)\tilde{y}_1^2 + (1-\kappa)\phi^2\right)}} \tag{8}$$

$$\lambda = \frac{\psi\phi}{2\sqrt{m\left(2A + (1+\kappa)\tilde{y}_1^2 + (1-\kappa)\phi^2\right)}}. \tag{9}$$

Proof. The solutions and proof are for period $t=2$. The derivation of equilibrium solutions for period $t=1$ is analogous. The insider submits a demand, x_2, that he believes will maximize his expected profit. To do this, he solves

$$\max_{x_2} E(x_2\left(\left(\tilde{v} - P_2\right)|\tilde{y}_1,\tilde{y}_2\right)\Big) = \max_{x_2} E\left(x_2\left(\tilde{v} - \left(\mu + \lambda\left(x_2 + \tilde{b}_2 - \tilde{s}_2\right)\right)|\tilde{y}_1,\tilde{y}_2\right)\right), \tag{10}$$

where Equation (4) has been substituted for P_2. Taking first-order conditions and solving for x_2, we have

$$x_2 = \frac{E\left(\tilde{v}|\tilde{y}_1,\tilde{y}_2\right) - \mu + \lambda\left(\hat{s}_2 - \hat{b}_2\right)}{2\lambda} = \frac{\tilde{y}_1 + \tilde{y}_2 - \mu + \lambda\left(\hat{s}_2 - \hat{b}_2\right)}{2\lambda}. \tag{11}$$

And so, if the linear conjectures hold,

$$\alpha = \frac{\tilde{y}_1 - \mu + \lambda\left(\hat{s}_2 - \hat{b}_2\right)}{2\lambda} \text{ and } \beta = \frac{1}{2\lambda}. \tag{12}$$

[22] Because $\tilde{y}_1$ is publicly revealed at $t = 2$, the risk-neutral insider does not need to consider period 2 trading when determining his period one demand.

The market-maker sets price equal to the expected value of $\tilde{v}$, given the order flow she observes. We can calculate

$$P_2 = E(\tilde{v}|\tilde{y}_1, d_2) = \tilde{y}_1 - \frac{\beta\phi^2\left(\alpha + \hat{b}_2 - \hat{s}_2\right)}{\beta^2\phi^2 + \sigma_{b2}^2 + \sigma_{s2}^2} + \frac{\beta\phi^2 d_2}{\beta^2\phi^2 + \sigma_{b2}^2 + \sigma_{s2}^2}. \tag{13}$$

So, if the conjectures hold,

$$\mu = \tilde{y}_1 - \frac{\beta\phi^2\left(\alpha + \hat{b}_2 - \hat{s}_2\right)}{\beta^2\phi^2 + \sigma_{b2}^2 + \sigma_{s2}^2} \text{ and } \lambda = \frac{\beta\phi^2}{\beta^2\phi^2 + \sigma_{b2}^2 + \sigma_{s2}^2}. \tag{14}$$

The four equations in (12) and (14) have four unknowns and are solved by Equations (6) through (9). Thus, the conjectures are fulfilled and an equilibrium exists.

Clearly, from the construction of the model, expected noise trader buying activity is increasing in contemporaneous trading volume and in the square of the previous day's price change. We illustrate this by simulating 100,000 realizations of our model under the assumption that $\phi = 2$, $A = 2$, $m = 2$, $\psi = 2$, and $\kappa = 0.5$.[23] As in our empirical analysis, we first sort the simulation realizations into deciles based on period 2 trading volume and period 1 price change and subdivide the largest and smallest return deciles and the largest volume decile into vingtiles. We then calculate period 2 noise trader buy-sell imbalances for each partition using the methodology described above in Section 3.

Our first, and only, proposition is that expected noise trader losses from period 2 to period 3 are greater when the attention level, $\tilde{y}_1^2$, is greater. When the level of attention trading is greater, so too is the volatility of noise trader demand. This makes it more difficult for the market-maker to detect insider trading. Insider expected profits increase and so do noise trader losses. Proposition 1 gives us the testable predictions that stocks more heavily bought by attention-driven investors will underperform those sold for stocks that have attracted more attention. Since expected noise trader losses are equivalent to expected insider profits and $\tilde{y}_1^2$ is our measure of the attention level, Proposition 1 can be expressed as:

Proposition 1.

$$\frac{\delta}{\delta\tilde{y}_1^2} E\left(x_2\left(\tilde{v} - P_2\right)|\tilde{y}_1\right) > 0 \tag{15}$$

Proof. Substituting from Equations (4) and (5) and for σ_{b2}^2 and σ_{s2}^2, we can write noise trader expected losses as

$$\begin{aligned} E\left(x_2\left(\tilde{v} - P_2\right)|\tilde{y}_1\right) &= E\left((\alpha + \beta\tilde{y}_2)(\tilde{y}_2 + \tilde{y}_1 - \mu - \lambda(\alpha + \beta\tilde{y}_2))\right) \\ &= \left(\beta - \lambda\beta^2\right)\phi^2 \\ &= \frac{\phi}{2\psi}\sqrt{m\left(2A + (1+\kappa)\tilde{y}_1^2 + (1-\kappa)\phi^2\right)}. \end{aligned} \tag{16}$$

The derivative of which, with respect to $\tilde{y}_1^2$, is positive, which is what we wished to show.

[23] Because $\tilde{b}_t$ and $\tilde{s}_t$ are distributed normally, negative realizations are possible. The likelihood of these depends upon the parameter values. There were no negative realizations of $\tilde{b}_t$ or $\tilde{s}_t$ in this simulation.

References

Bamber, Linda Smith, Orie E. Barron, and Thomas L. Stober. 1997. Trading volume and different aspects of disagreement coincident with earnings announcements. *Accounting Review* 72:575–97.

Barber, Brad M., and Terrance Odean. 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55:773–806.

Barber, Brad M., and Terrance Odean. 2001. Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics* 116:261–92.

Barber, Brad M., and Terrance Odean. 2002. Online investors: Do the slow die first? *Review of Financial Studies* 15:455–89.

Barber, Brad M., Terrance Odean, and Ning Zhu. 2006. Do noise traders move markets? SSRN working paper. http://ssrn.com/abstract=869827.

Busse, Jeff, and Clifton Green. 2002. Market efficiency in real time. *Journal of Financial Economics* 65:415–37.

Genesove, David, and Chris Mayer. 2001. Nominal loss aversion and seller behavior: Evidence from the housing market. *Quarterly Journal of Economics* 116:1233–60.

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

Grossman, Sanford J., and Joseph E. Stiglitz. 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70:393–408.

Grullon, Gustavo, George Kanatas, and James P. Weston. 2004. Advertising, breadth of ownership, and liquidity. *Review of Financial Studies* 17:439–61.

Heath, Chip, Steven Huddart, and Mark Lang. 1999. Psychological factors and stock option exercise. *Quarterly Journal of Economics* 114:601–27.

Heisler, Jeffrey. 1994. Loss aversion in a futures market: An empirical test. *Review of Futures Markets* 13:793–822.

Hirshleifer, David, James N. Myers, Linda A. Myers, and Siew Hong Teoh. 2003. Do individual investors drive post-earnings announcement drift? Direct evidence from personal trades. SSRN working paper, http://ssrn.com/abstract=299260.

Hou, Kewei, Lin Peng, and Wei Xiong. 2006. A tail of two anomalies: The implications of investor attention for price and earnings momentum. Working Paper, Ohio State University.

Karpoff, Jonathan M. 1987. The relation between price changes and trading volume: A survey. *Journal of Financial & Quantitative Analysis* 22:109–26.

Keim, Donald B., and Ananth Madhavan. 1995. Anatomy of the trading process: Empirical evidence on the behavior of institutional traders. *Journal of Financial Economics* 37:371–98.

Keim, Donald B., and Ananth Madhavan. 1997. Transactions costs and investment style: An inter-exchange analysis of institutional equity trades. *Journal of Financial Economics* 46:265–92.

Keim, Donald B., and Ananth Madhavan. 1998. The cost of institutional equity trades. *Financial Analysts Journal* 54:50–69.

Kyle, Albert S. 1985. Continuous auctions and insider trading. *Econometrica* 53:1315–35.

Lee, Charles M. C. 1992. Earnings news and small traders. *Journal of Accounting and Economics* 15:265–302.

Locke, Peter, and Steven Mann. 2000. Do professional traders exhibit loss realization aversion? SSRN working paper, http://ssrn.com/abstract=251942.

Mayshar, Joram. 1983. On divergence of opinion and imperfections in capital markets. *American Economic Review* 73:114–28.

Merton, Robert. 1987. A simple model of capital market equilibrium with incomplete information. *Journal of Finance* 42:483–510.

Miller, Edward M. 1977. Risk, uncertainty, and divergence of opinion. *Journal of Finance* 32:1151–68.

Odean, Terrance. 1998a. Are investors reluctant to realize their losses? *Journal of Finance* 53:1775–79.

Odean, Terrance. 1998b. Volume, volatility, price, and profit when all trades are above average. *Journal of Finance* 53:1887–934.

Odean, Terrance. 1999. Do investors trade too much? *American Economic Review* 1279–98.

Seasholes, Mark, and Guojun Wu. 2004. Profiting from predictability: Smart traders, daily price limits, and investor attention. SSRN working paper, http://ssrn.com/abstract=527182.

Shapira, Zur, and Itzhak Venezia. 2001. Patterns of behavior of professionally managed and independent investors. *Journal of Banking and Finance* 25:1573–87.

Shefrin, Hersh, and Meir Statman. 1985. The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance* 40:777–90.

Wolff, Edward N. 2004. Changes in household wealth in the 1980s and 1990s in the U.S. Working Paper No. 407, Levy Economics Institute of Bard College.