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

Brad M. Barber

Terrance Odean*

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* Barber is at the Graduate School of Management, University of California, Davis. Odean is at the Haas School of Business, University of California, Berkeley. We appreciate the comments of David Blake, Ken French, John Griffin, Andrew Karolyi, Sendhil Mullainathan, Mark Rubinstein, Brett Trueman and seminar participants at Arizona State University, the University of California, Irvine, the University of California, Berkeley, the Copenhagen Business School, Cornell University, Emory, Ohio State University, the Stockholm School of Economics, Vanderbilt, the Wharton School, the 2001 CEPR/JFI symposium at INSEAD, Mellon Capital Management, the National Bureau of Economic Research, and the Risk Perceptions and Capital Markets Conference, Northwestern University. We are grateful to the Plexus Group, to BARRA, and to the retail broker and discount brokers who provided us with the data for this study and to the Institute for Quantitative Research and the National Science Foundation (grant #SES-0111470) for financial support. Shane Shepherd, Michael Foster, and Michael Bowers provided valuable research assistance. All errors are our own. Brad Barber can be reached at (530) 752-0512 or bmbarber@ucdavis.edu; Terrance Odean can be reached at (510) 642-6767 or odean@haas.berkeley.edu.

Abstract

We test the hypothesis that individual investors are more likely to be net buyers of attention-grabbing stocks than are institutional investors. We speculate that attention-based buying is a result of the difficulty that individual investors have searching the thousands of stocks they can potentially buy. Individual investors don't face the same search problem when selling, because they tend to sell only a small subset of all stocks—those they already own. We look at three indications of how likely stocks are to catch investors' attention: daily abnormal trading volume, daily returns, and daily news. We calculate net order imbalances for more than 66,000 individual investors with accounts at a large discount brokerage, 647,000 individual investors with accounts at a large retail brokerage, 14,000 individual investor accounts at a small discount brokerage, and 43 professional money managers. Individual investors tend to be net purchasers of stocks on high attention days—days that those stocks experience high abnormal trading volume, days following extreme price moves, and days on which stocks are in the news. Institutional investors are more likely to be net buyers on days with low abnormal trading volume than on those with high abnormal trading volume. Their reaction to extreme price moves depends on their investment style. The tendency of individual investors to be net buyers of attention-grabbing stocks is greatest on days of negative returns.

How do investors choose the stocks they buy? Are their choices so randomly idiosyncratic that, in aggregate, they cancel out each other and thus have no influence on stock prices? Or do the purchase patterns of investors—even those with heterogeneous beliefs—aggregate in a way that may move price? Several studies document that investors are systematically reluctant to sell stocks for a loss (e.g., Statman and Shefrin, 1985, Odean, 1998a, Grinblatt and Keloharju, 2001). Less is known about how they make purchases. In this paper, we test the proposition that individual investors simply buy those stocks that catch their attention. 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. Systematic buying behavior, like systematic selling, has the potential to influence prices, especially for assets heavily traded by individual investors such as the common stock of small capitalization firms and of firms with recent initial public offerings.

In contrast to our findings, many theoretical models of investor trading 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.[2] 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 over 7,000 U. S. 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 10 alternatives than 100.

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

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.

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.[3] Second, most individual investors only sell stocks that they already own, that is, they don't sell short.[4] 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 losers, thereby postponing taxes; behaviorally motivated investors are likely to sell past winners, thereby postponing the regret associated with realizing a loss (see Statman and Shefrin, 1985). Thus, to a large extent, individual investors are concerned about the future returns of the stocks they buy but 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. First, unlike individual investors, institutions do often face a significant search problem when selling. Second, attention is not as scarce a resource for institutional investors as it is for individuals.

[3] On average during our sample period, the mean household in our large discount brokerage dataset held 4.3 stocks worth $47,334; the median household held 2.61 stocks worth $16,210.
[4] 0.29 percent of positions are short positions for the investors in the large discount brokerage dataset that we describe in Section II. When the positions are weighted by their value, 0.78 percent are short.

Like individuals, institutions also face many choices when purchasing, but, unlike individuals, they also face many choices when selling. Institutional investors, such as hedge funds, routinely sell short. For these investors, the search set for purchases and sales is identical. Even institutions that do not sell short face far more choices when selling than do most individuals, simply because they own much larger portfolios than do most 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. While individuals, too, can use computers or pre-selection criteria, on average, they are less likely to do so.

In this paper, we test the hypotheses that (1) the buying behavior of individual investors is more heavily influenced by attention than is their selling behavior and that (2) the buying behavior of individual investors is more heavily influenced by attention than is the buying behavior of professional investors.

One measure of the extent to which a stock grabs investors' attention is its abnormal trading volume. Imagine standing on a street and observing a large crowd gathered at one end of the street and nobody stopped at the other end. You don't know why the crowd has gathered, maybe to watch street performers, maybe to help an old man who had a heart attack. You do know that an attention-grabbing event is taking place on the end of the street where the crowd has gathered not the end without a crowd. Similarly when, as researchers, we observe abnormal trading volume in a stock, we know that something has happened to grab investors' attention—though we may not know what that something is. Abnormal trading volume serves as a proxy for the unobserved attention-grabbing event. As discussed above, we believe that attention is a greater determinant of what individual investors buy than of what they sell. Thus, individual investors will actively buy stocks with unusually high trading volume. They may also sell highly traded stocks, however, selling won't be as influenced by attention and will not increase as much when trading volume is abnormally high.

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 (inclusive of market-makers) will exhibit a lower tendency to buy, rather than sell, on days of high abnormal volume and a reverse tendency on days of abnormally low volume. (Exceptions will arise when the event driving abnormal volume coincides with the purchase criteria that the professional investor is pursuing.)

We examine the buying and selling behavior associated with abnormal trading volume 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.

As predicted, individual investors tend to be net buyers on high attention days; for example, investors at the large discount brokerage make nearly twice as many purchases as sales of stocks experiencing unusually high trading volume (e.g, the highest five percent).[5] The buying behavior of the professionals is least influenced by attention.

In addition to abnormal trading volume, another phenomenon that is likely to coincide with salient events—or be salient itself—is an extreme one day price move. A stock that soars or dives catches peoples' attention. News agencies routinely report the prior day's big winners and big losers. Furthermore, large price moves are often associated with salient announcements or developments. We sort stocks based on one-day returns and examine investors' buying and selling behavior on the subsequent day.[6] We anticipate—and find—

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

[6] We report order imbalances for stocks sorted and partitioned on same day news and same day abnormal trading volume, and previous day's return. We do not report order imbalances for stocks sorted on same day

that attention driven investors tend to be net buyers of both the previous day's big winners and big losers. For example, investors at the large discount brokerage firm are nearly twice as likely to buy as to sell a stock with an extremely poor performance (lowest 5 percent) the previous day.

Finally, news catches investors' attention. We anticipate—and find—that attention driven investors tend to be net buyers of companies on days that those companies are in the news.

The plan of the paper is as follows. We discuss related research in section I. We describe the four datasets in section II, and our methodology in section III. We present results in section IV, discuss an alternative hypothesis in section V, consider some implications of our findings in section VI, and conclude in section VII.

I. 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), company stock options (Heath, Huddart, and Lang, 1999), and futures (Heisler, 1994; Locke and Mann, 1999) (also see Shapira and Venezia, 1998). Analyzing comprehensive data on investors in the Finnish stock market, Grinblatt and Keloharju (2001) confirm that individual Finnish investors are less likely to sell their losing investments than winners.

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 fivefold (on average) in the minutes following the mention (Busse and

returns because of potential endogeneity problems. While we argue that an extreme price move may attract buyers, clearly buyers could also cause price moves. Our results are qualitatively similar when when we calculate imbalances the same day that we sort on returns., Green (2002)). Yet, for every buyer there is a seller. In general, these studies to not investigate who is buying and who is selling—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 individual investors—those who place market orders of less than $10,000—are net buyers subsequent to both positive and negative earnings surprises. Hirshleifer, Myers, Myers, and Teoh (2002) also 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.

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 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 disparity between buying and selling decisions for individual investors and the search problem they face when choosing from among thousands of stocks. 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 predominantly buying 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 non-attention-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 sub-optimally. Odean (1999) and Barber and Odean (2000, 2001a, 2001b) find that, on average, individual investors do trade sub-optimally, lowering their expected returns through excessive trading.

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, that happen to catch their attention. Thus their purchases will not be biased toward attention-grabbing stocks.

II. 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.[7] The data include all 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, while 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 in other than individual common stocks. Roughly 60 percent of the market value in these households' accounts was held in common stocks. There were over 3 million trades in all securities; common stocks accounted for slightly more than 60 percent of all trades. During our sample

[7] 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.

period, the average household held 4.3 stocks worth $47,334, though each of these figures is positively skewed. The median household held 2.61 stocks worth $16,210. 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 data set 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 June 15, 1999. Accounts classified by the brokerage firm as professionals are excluded from our analysis.[8] 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 data set 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 non-discretionary 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 over 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.

The fourth data set was compiled by the Plexus Group as part of their advisory services for their institutional clients. The data include daily trading records for 43

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[8] We analyze the accounts of professional investors separately. There are, however, not enough data to achieve statistically significant results.

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 dataset, these money managers are classified as "momentum," "value," and "diversified."[9] During our sample period, the eighteen 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 eleven 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 fourteen diversified managers make 312,457 purchases with a mean value of $450,474 and 202,147 sales with a mean value of $537,947.

III. Methodology

A. 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

$$AV_{it} = \frac{V_{it}}{\overline{V}_{it}} \tag{3.1}$$

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 NYSE, ASE, and NASDAQ stocks and

$$\overline{V}_{it} = \sum_{d=t-252}^{t-1} \frac{V_{id}}{252}\,. \tag{3.2}$$

[9] 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 classification correspond to our "momentum," "value," and "diversified" classifications.

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

$$OI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}} \tag{3.3}$$

where n_{pt} is the number of stocks in partition p on day t, NB_{it} the number of purchases of stock i on day t, and NS_{it} the number of sales of stock i on day t. We calculate the time series mean of the daily order imbalance (OI_{pt}) for the days that we have trading data for each investor type. Note that throughout the paper our measure of order 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 order 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 3.3. Note that while total buys and sells increase as volume increases, on a value weighted basis, aggregate buys and sells will increase equally. Thus aggregate value weighted (executed) order imbalance remains zero as abnormal volume increases, and how the order 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 order imbalance. 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.

B. Return Sorts

Investors are likely to notice when stocks have extreme one day returns. Such returns, whether positive or negative, will most often be associated with news about the firm. The news driving 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 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 order 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. Firstly, 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. Secondly, order imbalances could cause contemporaneous price changes. Thus, examining order imbalances subsequent to returns, removes a potential endogeneity problem.[10] Our results are qualitatively similar when we sort on same day returns.

Each day (*t-1*) we sort all stocks for which returns are reported in the CRSP NYSE/AMEX/NASDAQ daily returns file into ten deciles based on the one day return. We further split decile one (lowest returns) and decile ten (highest returns) into two vingtiles. We then calculate the time series mean of the daily order imbalance for each partition on the day following the return sort. This calculation is analogous to that for our sorts based on abnormal volume.[11]

[10] 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 is purchases causes contemporaneous news stories. Nor does the percentage of individual investors' (or institutional investors') trades that is purchases cause abnormal trading volume.

[11] 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 order 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 substitute this average in place of the actual 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

C. News Sorts

Firms that are in the news are more likely to catch investors' attention than those that are not. We partition stocks into those for which there is a news story that day and those with no news. Our news dataset is the daily news feed from Dow Jones News Service. The data begin in 1994. Due to how the data were collected and stored some days are missing from the data. The Dow Jones news feed includes the ticker symbols for each firm mentioned in each article. On an average day, our dataset records no news for 91% of the firms in the CRSP database. We calculate order imbalances for each firm's stock as described in Section IIIa.

D. Example

Imagine, for example, a market with only four stocks, A, B, C, and D, and only four individual investors, 1, 2, 3, and 4. Each investor owns at least one share of one stock. Each stock is equally likely to be owned by any investor. At the beginning of the day, the market receives bad news about stock A, causing its price to fall sharply for the day, no news about stocks B and C whose prices changes for the day are small, and good news about stock D, causing its price to rise sharply for the day. Two investors receive positive liquidity shocks leading them to each buy one share of stock; two investors receive negative liquidity shocks leading them to each sell one share of stock. The individual investors trade with institutional investors, including market-makers, thus there is no need for their purchases to balance their sales. In this simple example, assume that the two investors who buy stock each buy one of the attention-grabbing stocks (i.e., A or D). The investors who sell each sell one of the stocks they own. Thus stocks A, B, C, and D are each sold with equal probability. Ignoring days on which a particular stock is neither purchased or sold—as we do in our study—we can calculate the expected individual investor order imbalance for each of these stocks. This is 21.33/55 for stocks A and D and –1 for stocks B and C. Obviously, the expected trading

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

where S_o is the number of stocks with zero return on day *t-1*. There is an analogous calculation for sales.

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*.

volume for stocks A and D is greater than for stocks B and C. Figure 1a plots order imbalance for stocks sorted on expected trading volume. Note that we would get this same upward sloping if we sorted stocks on whether or not they were in the news and then plotted expected order imbalance. In Figure 1b, we first sort on return—A very negative, D very positive, B and C somewhere in between A and D—and then plot expected order imbalance.[12] The graph is convex and U-shaped.

E. Performance Analysis

To assess whether investors are benefiting from their attention-based trading we calculate style-adjusted alphas based on Fama and French's (1993) three-factor model. There are two ways in which investors' returns could benefit from what appears to be attention-based trading. Firstly, they could benefit if the high-attention stocks they bought subsequently outperformed the high-attention stocks they sold. Secondly, since they are net buyers of high-attention stocks, investors would also benefit if the high-attention stocks they bought subsequently outperformed the market, even if purchases and sales performed similarly. To examine these possibilities, we calculate annual calendar time returns for stocks bought and stocks sold in high-attention partitions.

On each day, we construct a portfolio comprised of those stocks purchased in a high-attention partition within the last year (252 trading days). The return on the portfolio is calculated based on the value of the initial purchase as:

$$R_t^b = \frac{\sum_{i=1}^{n_{bt}} x_{it} \cdot R_{it}}{\sum_{i=1}^{n_{bt}} x_{it}} \tag{3.4}$$

where R_{it} is the gross daily return of stock i on day t, n_{bt} is the number of different stocks purchased during the past year, and x_{it} is the compound daily return of stock i from the close of trading on the day of the purchase through day $t-1$ multiplied by the value of the purchase. For each high-attention partition, three portfolios are constructed: one for the purchases (R_t^b),

[12] In this simple example we plot same day expected order imbalance, in the results section we report order

one for the sales (R_t^s), and a value-weighted portfolio of all firms within the partition (assuming a holding period of one year).

We calculate alphas adjusted for market risk and for the return differentials associated with small versus large firms, and value versus growth firms by estimating the following three-factor monthly time-series regression:

$$\left(R_t^i - R_{ft}\right) = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + v_i VMG_t + \varepsilon_{it} \tag{3.5}$$

where

R_{ft} = the monthly return on T-Bills,[13]

R_{mt} = the monthly return on a value-weighted market index,

SMB_t = the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of big stocks,[14]

VMG_t = the return on a value-weighted portfolio of value (i.e., high book-to-market) stocks minus the return on a value-weighted portfolio of growth (i.e., low book-to-market) stocks,[15]

α_i = the intercept,

β_i = the market beta,

s_i = coefficient of tilt towards small and away from large firms,

v_i = coefficient of tilt towards value and away from growth firms, and

ε_{it} = the regression error term.

The subscript *i* denotes parameter estimates and error terms from regression *i*, where we estimate twelve regressions—one for stocks purchased, one for stocks purchased less stocks sold, and one for a value-weighted portfolio of all stocks in each of four partitions that we analyze: the top decile of stocks sorted on abnormal trading volume, the top and bottom deciles of stocks sorted on the previous days returns, and stocks with news coverage.

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imbalance the day following returns so as to avoid endogeneity issues.

[13] The return on T-bills is from Stocks, Bonds, Bills, and Inflation, 1997 Yearbook, Ibbotson Associates, Chicago, IL.

[14] The construction of this portfolio is discussed in detail in Fama and French (1993). We thank Kenneth French for providing us with these data.

In each regression the estimate of β_i measures portfolio risk due to covariance with the market portfolio. The estimate of s_i measures the portfolio's small firm tilt or risk; a larger value of s_i denotes increased exposure to small stocks. Fama and French (1993) and Berk (1995) argue that firm size is a proxy for risk.[16] The estimate of v_i measures the tilt of the portfolio towards value and away from growth firms. Finally, the intercept, α_i, is an estimate of style-adjusted return.

IV. Results

A. Volume Sorts

Trading volume is one indicator of the attention a stock is receiving. Table I presents order imbalances for stocks sorted on the current day's abnormal trading volume. Order imbalance is 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. Investors at the large discount brokerage display the greatest amount of attention-based buying. When imbalance is calculated by number of trades (column two), 18.15 percent fewer of their trades are purchases than sales for stocks in the lowest volume decile. For stocks in the highest volume vingtile, 29.5 percent more of their trades are purchases than sales. Their order imbalance rises monotonically with trading volume. When imbalance is calculated by value of trades (column three), 16.28 percent fewer of their trades are purchases than sales for stocks in the lowest volume decile. For stocks in the highest volume vingtile, 17.67 percent more of their trades are purchases than sales. Order imbalance increases nearly monotonically with trading volume. Looking at the fourth through seventh columns of Table 1, we see that the net buying behavior of investors at the large retail broker and the small discount brokerage is similar to that of investors at the large discount brokerage.

[15] Fama and French (1993) denote this portfolio as *HML*. We appreciate Jay Ritter's suggestion that VMG is more descriptive.

[16] Berk (1995) points out that systematic effects in returns are likely to appear in price, since price is the value of future cash flows discounted by expected return. Thus size and the book-to-market ratio are likely to correlate with cross-sectional differences in expected returns. Fama and French (1993) also claim that size and the book-to-market ratio proxy for risk. Not all authors agree that book-to-market ratios are risk proxies (e.g., Lakonishok, Shleifer, and Vishny (1994)). Our qualitative results are unaffected by the inclusion of a book-to-market factor.

Our principal objective is to understand how attention affects the purchase decisions of all investors. Calculating order imbalance 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 processes, calculating order imbalance by number of trades may be most appropriate. Figure 2a graphs the order imbalance based on number of trades for investors at the large discount brokerage, the large retail brokerage, and the small discount brokerage. Note that the plots are upward sloping as they were in our simple example (Figure 1a).

The last six columns of Table 1 and Figure 2b present the order 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 order imbalance is 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.

B. 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 II and Figures 3a and 3b present order imbalances for stocks sorted on the previous day's return. Order imbalance is reported for 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.

Investors at the large discount brokerage display the greatest amount of attention-based buying for these returns sorts. When calculated by number of trades, the order imbalance of investors at the large discount brokerage is 29.4 percent for the vingtile of stocks with the worst return performance on the previous day. Imbalance drops to 1.8 percent in the eighth return decile and rises back to 24 percent for stocks with the best return performance on the previous day. We see in Figure 3a, as was the case in our simple example

(Figure 1b), that the order imbalance of these investors is U-shaped when stocks are sorted on the previous day's return.[17] They buy attention-grabbing stocks. When imbalance is calculated by value of trades, the order imbalance of these investors is 29.1 percent for the vingtile of stocks with the worst return performance on the previous day. Imbalance drops to negative 8.6 percent in the eighth return decile and rises back to 11.1 percent for stocks with the best return performance on the previous day.

In Figure 3a, 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 II and in Figure 3b, 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. While one might interpret purchases of yesterday's winners by momentum managers and the purchases of yesterday's losers by the 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.

C. News Sorts

Table III reports average daily order imbalance 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

[17] Order imbalances are very similar when we partition stocks on same day's return rather than on the previous day's return.

than those that are not.[18] When calculated by number for the large discount brokerage, order imbalance is –2.70 percent for stocks out of the news and 9.35 percent for those stocks in the news. At the large retail brokerage, order imbalance is –2.40 percent for stocks out of the news and 16.95 percent for those in the news.

Table III also reports order 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. While both the disposition effect and limit orders may contribute to the greater order imbalance on negative return days, we suspect that limit orders are the primary cause.

To test the robustness of our news sort results, we calculate order imbalances for news and no-news days during four day periods surrounding earnings announcements (the day prior to the announcement, the day of the announcement, and the two days subsequent to the announcement) and during non-earnings announcement periods. For both earnings and non-earnings periods, investors at all three brokerages have a greater propensity to buy (rather than sell) stocks that are in the news.[19]

[18] Choe, Kho, and Stulz (2000) find that individual investors in Korea buy in the days preceding large one day price increases and sell preceding large one day losses. Large one day price moves are likely to be accompanied by news. Choe, Kho, and Stulz point out that the savvy trading of Korean individual investors could result from insider trading.

[19] During earnings announcement periods, order imbalance calculated by number of trades at the large discount brokerage is 11.49 percent on days with news and 5.14 percent on days without news; at the small discount brokerage 8.57 percent and -2.67 percent, respectively; and at the large retail brokerage, 7.52 percent and 1.63 percent. During non-earnings announcement periods, order imbalance at the large discount brokerage is 9.01

D. Size Partitions

To test whether our results are driven primarily by small capitalization stocks, we calculate order 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's return, and same day news. We then calculate imbalances separately for small, medium, and large capitalization stocks using the same break points to form abnormal volume and return deciles for all three size groups. We use monthly New York Stock Exchange market equity breakpoints to form our size groups.[20] Each month we classify all stocks (both NYSE listed and non-listed stocks) with market capitalization less than or equal to the 30th percentile break point as small stocks, stocks with market capitalization greater than the 30th percentile and less than or equal to the 70th percentile as medium stocks, and stocks with market capitalization greater than the 70th percentile as large stocks. Table IV, reports order imbalances by size group for abnormal volume, return, and news sorts. To conserve space we report imbalances for the investors most likely to display attention-based buying: those at the large discount brokerage. Results for the large retail and small discount brokerages are qualitatively similar.[21]

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 post earning announcement drift, are greater for small capitalization stocks than for large stocks. Some researchers have suggested that these phenomena may be caused by the trading behavior of individual investors. We find, however, that attention-based buying by individuals is as strong for large capitalization stocks as for small stocks. It may be that the individual investor's psychology of investing is similar for large and small stocks but

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percent on days with news and 2.53 percent on days without news; at the small discount brokerage, 6.22 percent and –0.75 percent; and at the large retail brokerage 17.32 percent and –2.51 percent.

[20] We thank Ken French for supplying market equity breakpoints. These breakpoints are available and further described at http://web.mit.edu/kfrench/www/Data_Library/det_me_breakpoints.html.

[21] The only significant exception to this pattern is that order 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.

that, due to trading costs and other limits of arbitrage, the impact the individual investor's psychology is greater for small stocks.

E. Performance

The goal of our paper is to test the attention hypothesis of buying behavior for different groups of investors. We are not comparing the performance of these groups. Some may wonder, however, whether the buying behavior we are attributing to attention is actually rationally optimal for investors. Do investor's earn superior returns as a result of attention-based buying?

Investors' returns could benefit from what appears to be attention-based trading if, in high-attention partitions, the stocks they bought subsequently outperformed the stocks they sold or if the stocks they bought in these partitions subsequently outperformed the overall market. Table V reports three-factor alphas and standard errors for portfolios of stocks bought minus stocks sold in high-attention partitions—based on abnormal volume sorts, prior day returns sorts, and news sorts. Table V also reports three-factor alphas for the portfolios of stocks bought in the high-attention partitions and, for reference, a value-weighted portfolio of all stocks within the partition. (All portfolios assume a holding period of one year.) We present results only for the large discount brokerage, since the time periods of our data for the large retail and small discount brokerages are too short to test for significant abnormal performance.[22]

All of the alphas reported in the last two columns of Table V are negative, most reliably so. It does not appear that the investors at the large discount brokerage are benefiting financially from attention-based buying.

[22] The time period for our news sort for the large discount brokerage data is also shorter than the periods for the abnormal volume and returns sorts. Consequently, the three-factor alphas for the news sort are not significantly different from zero. Gadarowski (2001) reports that firms with high news coverage underperformed over a two year horizon during the period 1980 through 1994. Chan (2001), using a different methodology, documents no significant abnormal returns for firms with high news coverage, though he argues there is continued negative drift for stocks with bad news.

V. An Alternative Hypothesis

An alternative potential explanation for our findings is that different investors interpret attention-grabbing events such as news differently and so such events lead to greater heterogeneity of beliefs. 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. On average, bullish individuals and institutions buy while bearish institutions, but not individuals, sell. Thus attention-grabbing events are associated with net buying by individuals, not because individuals are buying what catches their attention, but because attention-grabbing events are increasing heterogeneity of beliefs while limited portfolios and short sale constraints restrict would be sellers. As attention-grabbing events become less recent, they become less salient thereby reducing heterogeneity of beliefs during non-event periods.

While increased heterogeneity of beliefs and selling constraints may contribute to net buying by individuals around attention-grabbing events, we don't think that this is the whole story. We believe that attention plays a major role in determining what stocks investors buy. We further test our attention hypothesis by examining how individual investors buy and sell the stocks that they already own.

Under this alternative hypothesis, attention-grabbing events increase the heterogeneity in investors' beliefs thus leading to trade. Investors without selling constraints are as likely to sell as they are to buy. Investors who already own a stock can sell it. Thus, under this alternative hypothesis, we would expect attention-grabbing events to increase 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. As discussed above, most individual investors do not face a formidable search problem when choosing a stock to sell, but they do when buying. Stocks they already own compete with thousands of other stocks as potential purchases. 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 to buy stocks they already own.

Under the attention hypothesis, however, the order imbalance of stocks that investors already own should be greater on days that those stocks are attention-grabbing.

In Table VI, we report order 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 I, II, and III. 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, order imbalances do not increase as they do for all stocks, regardless of current ownership (as reported in Table II). It is likely that for stocks investors already own, the disposition effect influences their purchases as well as their sales. Odean (1998a) reports that investors are more likely to purchase additional shares of stocks they already own if the share price is below, rather than above, their original purchase price. As predicted by Prospect Theory (Kahneman and Tversky, 1979), investors assume more risk when in the domain of losses than when in the domain of gains. The results in Table VI, Panel C are consistent with this.

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 are purchases rather than sales on high attention days.

VI. Discussion

If the trading of individual investors influences asset prices, what might we expect to be the effects of attention-based buying on asset prices? High attention days are likely to be days on which investors receive information. Thus, attention-based buying may influence the rate at which information is incorporated into prices. This influence will probably be most discernable for small stocks, which tend to have greater individual investor ownership.

We have discussed three factors that affect order imbalance: attention, the disposition effect, and limit orders. These factors have similar effects on order imbalance following bad news, but have offsetting effects on order imbalance following good news. Investors tend to be net buyers on high attention days, regardless of whether these days are associated with positive or negative information. Investors may be less willing to sell stocks when prices fall due to the disposition effect. And investors may buy in falling markets and sell in rising markets as limit orders—some poorly monitored—execute.

Investors tend to be net buyers when their attention is attracted by negative information. They are less willing to sell when a stock drops in price. And their limit orders to buy execute as price drops. Thus, attention-based buying, the disposition effect, and limit orders all work to increase the ratio of purchases to sales by individual investors in response to negative information. This slows the price fall and partially delays the incorporation of information into price. If, in time, prices do fully reflect information, the partial delay will cause returns to be positively serially correlated.

Investors also tend to be net buyers when their attention is attracted by positive information. They are, relatively, more willing to sell stocks that have risen in price. And sell limit orders execute as price rises. Thus attention-based buying, the disposition effect, and limit orders are offsetting in their effects on order imbalance in response to positive information. While attention-based buying is likely to hasten or even exaggerate the impact of positive information, the disposition effect and limit orders will dampen that impact.

Hong, Lim, and Stein (2000) report that stocks with less analyst coverage exhibit more positive serial correlation in returns and that this positive serial correlation is greatest for stocks with negative returns. Chan (2001) documents similar results following the release of bad news. These studies propose that investors are slow to react to bad news. Our findings suggest an alternative mechanism. The individual investors in our sample behave as contrarians when faced with bad news. They don't underreact to information (i.e., sell too little), rather they counteract it (i.e., buy on bad news). They do not appear to be reacting slowly to the dissemination of information—we observe contrarian buying the same day that news stories appear. Our belief is that investors slow the incorporation of negative information into prices not because they are slow to learn about or fully appreciate information, but because attention-based buying, the disposition effect, and unmonitored limit orders work in tandem to offset information based selling.

How attention-based buying, the disposition effect, and unmonitored limit orders affect the incorporation of negative news will depend, among other things, on the time horizons over which these phenomena operate. In this paper, we document same day and next day attention effects. And the triggering of unmonitored limit orders by one day price moves endures, of course, for but one day. While the disposition effect—investors' reticence to sell for a loss—is is likely to be more persistent.[23] .

Demar and Lewellen (2001) find that website traffic for internet firms increases subsequent to underpriced initial public offerings (IPOs). The web traffic growth is positively and significantly associated with initial returns. Demar and Lewellen speculate that IPO underpricing attracts media attention and creates valuable publicity. Just as publicity may help firms to sell their goods to the public, it may also help them to sell their stock. If underpricing leads to publicity and publicity catches the attention of individual investors, underpriced IPOs may attract additional buyers who buy even after the stock is no longer underpriced. If the purchases of attention motivated buyers are not offset by sales or foregone purchases of other investors, the underpriced IPOs price may rise higher than they otherwise would.

VII. Conclusion

For those who invest in individual common stocks, the choice of which stocks to buy is far different—and perhaps more challenging—than the choice of which to sell. When selling, most investors consider only stocks they already own. These are typically few in number and can be considered one by one. The tax savvy investor will tend to sell stocks for a loss; emotionally motivated investors may cling to their losers and sell winners. Choosing which stock to buy presents investors with a huge search problem. There are thousands of possibilities. Human beings are limited in their mental processing abilities. Without the aid of a computer, it would be extremely time consuming, if not impossible, for most investors to evaluate the merits of every available common stock.

We argue that many investors solve this search problem by only considering for purchase those stocks that have recently caught their attention. While they don't buy every stock that catches their attention, they buy far fewer that don't. 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 likely to indulge in attention-based purchases. With more time and resources, professionals are able to continuously monitor 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-based 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-based 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 may even attract attention in their own right. And we sort on whether or not a firm is in the news.

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[23] See Weber and Zuchel (2001) and Grinblatt and Han (2002).

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

Individual investor attention-based buying is similar for large capitalization stocks as for small stocks. In contrast, many observed anomalies, such as price momentum and post-earnings announcement drift, are stronger for small stocks. If individual investors contribute to these anomalies, differences in the anomalous behavior of large and small stocks could be due to differences in the individual investor's psychology of trading these stocks or in differences in the limits of arbitrage available to other investors. Our results favor the limits of arbitrage explanation.

Investors prone to engaging in attention-based buying do not benefit from doing so. Based on our abnormal volume and extreme return sorts, the attention-grabbing stocks that they buy do not outperform the market; nor do the attention-grabbing stocks they buy outperform those they sell.

In previous work, we have 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). 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.

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TABLE I: Order imbalance by Investor Type for Stocks Sorted on the Current Day's Abnormal Trading Volume

Stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (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. Order imbalances are reported for the trades of six groups of investors, investors at 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 June 15, 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.

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

TABLE II: Order imbalance by Investor Type for Stocks Sorted on the Previous Day's Return

Stocks are sorted daily into deciles on the basis on 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. Order imbalances are reported for the trades of six groups of investors, investors at 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 June 15, 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.

	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)	29.4	29.1	25.79	22.89	17.32	14.9	-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	19.2	16.2	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	13.7	8.8	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	8.9	3.1	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	3.9	-3.3	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	4.1	-3.6	-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	3.7	-4.2	-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	2.0	-7	-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	1.8	-8.6	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	6.7	-4.8	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	13.4	3.2	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)	24	11.1	9.01	-7.93	3.8	-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)

TABLE III: Order Imbalance by Investor Type for Stocks Sorted on the Current Day's News.

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 per cent of stocks. Order 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 June 15, 1999), and institutional money managers (January 1993 through March 1996) classified by the Plexus Group as following momentum, value, and diversified strategies. Order 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.

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage		Momentum Managers		Value Managers		Diversified Managers	
Partition	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	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)

TABLE IV: Order Imbalance 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.

In Panel A, stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (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 B, stocks are sorted daily into deciles on the basis on 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 per cent 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 30th percentile break point as small stocks, stocks with market capitalization greater than 30th percentile and less than or equal to the70th percentile as medium stocks, and stocks with market capitalization greater than the 70th percentile as large stocks. Order 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.

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

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

Panel C: Order Imbalance 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 All Days	19.87 (1.47)	14.59 (1.85)	13.38 (1.15)	3.87 (1.62)	6.52 (0.85)	-1.35 (0.97)
No News All Days	7.53 (0.48)	2.82 (0.70)	3.12 (0.57)	-4.83 (0.88)	-2.91 (0.67)	-9.86 (0.94)

Table V. Three-factor alphas for portfolios of stocks purchased and portfolios of stocks purchased minus those sold in high-attention partitions based on abnormal volume sorts, the previous day's return sorts, and new coverage.

Trades data are from a large discount broker (January 1991 through November 1996). Stocks are sorted daily on the basis on the current day's abnormal trading volume, the previous day's return, and the current day's news. 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. Stocks are sorted daily into deciles on the basis on the previous day's return as reported in the CRSP daily stock return files for NYSE, ASE, and NASDAQ stocks. Finally, stocks are partitioned daily into those with stories (as reported by the Dow Jones News Service) that day. "All Stocks" is a value-weighted portfolio of stocks within a partition. Stocks purchased is a portfolio of stocks bought within the partition, while stocks sold is a portfolio of stocks sold within the partition. All portfolios are rebalanced daily assuming a holding period of one year. The purchase and sale portfolios are constructed using the value of purchases and sales, respectively. Intercept estimates for the three-factor model are those from a time-series regression of excess monthly return on the market excess return $(R_{mt} - R_{ft})$, a zero-investment size portfolio (SMB_t), and a zero-investment value minus growth portfolio (VMG_t): $\left(R_t^p - R_{ft}\right) = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i SMB_t + v_i VMG_t + \varepsilon_{it}$. T-statistics appear in parentheses.

	All Stocks	Portfolio of Stocks Purchased	Portfolios of Stocks Purchased minus Portfolio of Stocks Sold
Abnormal Volume Sort Top Decile	0.007 (0.15)	-0.363 (-1.22)	-0.308 (-2.77)
Return Sort Bottom Decile -- Most Negative	-0.270 (-2.17)	-0.523 (-1.59)	-0.072 (-0.50)
Return Sort Top Decile – Most Positive	-0.221 (-1.94)	-0.672 (-1.97)	-0.275 (-3.48)
News Sort Stocks with News	0.154 (1.13)	-0.238 (-0.29)	-0.123 (-0.54)

TABLE VI: Order Imbalance 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.

In Panel A, stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (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 B, stocks are sorted daily into deciles on the basis on 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). Order 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 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.

Panel A: Order imbalance 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)

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

Panel C: Order Imbalance 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 All Days	-40.91 (0.79)	-42.36 (0.94)	-15.38 (0.94)	-23.95 (0.98)	-22.14 (0.91)	-22.02 (1.52)
No News All Days	-45.05 (0.52)	-45.98 (0.77)	-21.42 (0.92)	-25.46 (1.02)	-32.77 (1.00)	-33.68 (1.52)

Figure 1: Expected order imbalance for example in Section IIId

Figure 1a

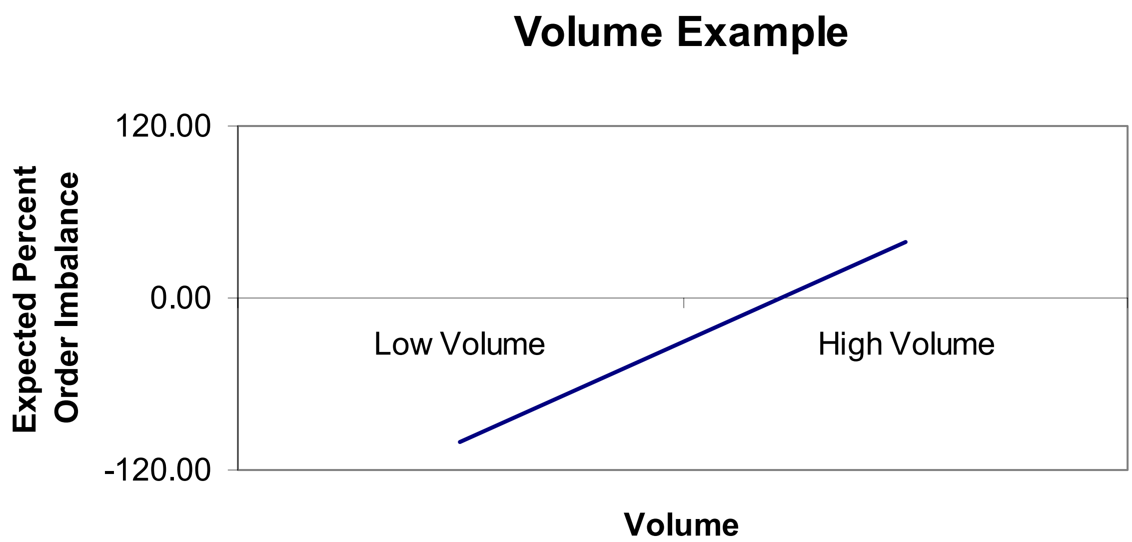

Figure 1b

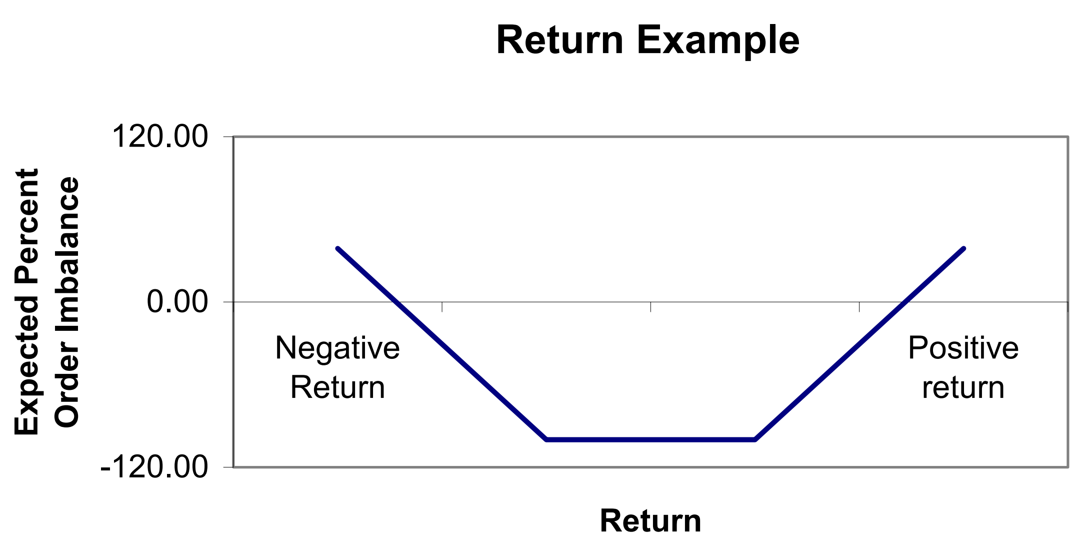

Figure 2: Order imbalance by Number of Trades for Stocks Sorted on the Current Day's Abnormal Trading Volume

Stocks are sorted daily into deciles on the basis on the current day's abnormal trading, The decile of highest abnormal trading is split into two vingtiles (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. Figure 2a graphs order imbalances for investors at a large discount brokerage (1991-1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount broker (January 1996 through June 15, 1999). Figure 2b graphs order imbalance for institutional money managers (January 1993 through March 1996) classified 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. The figure depicts the mean for each time-series of daily imbalances for a particular investor group.

Figure 2a

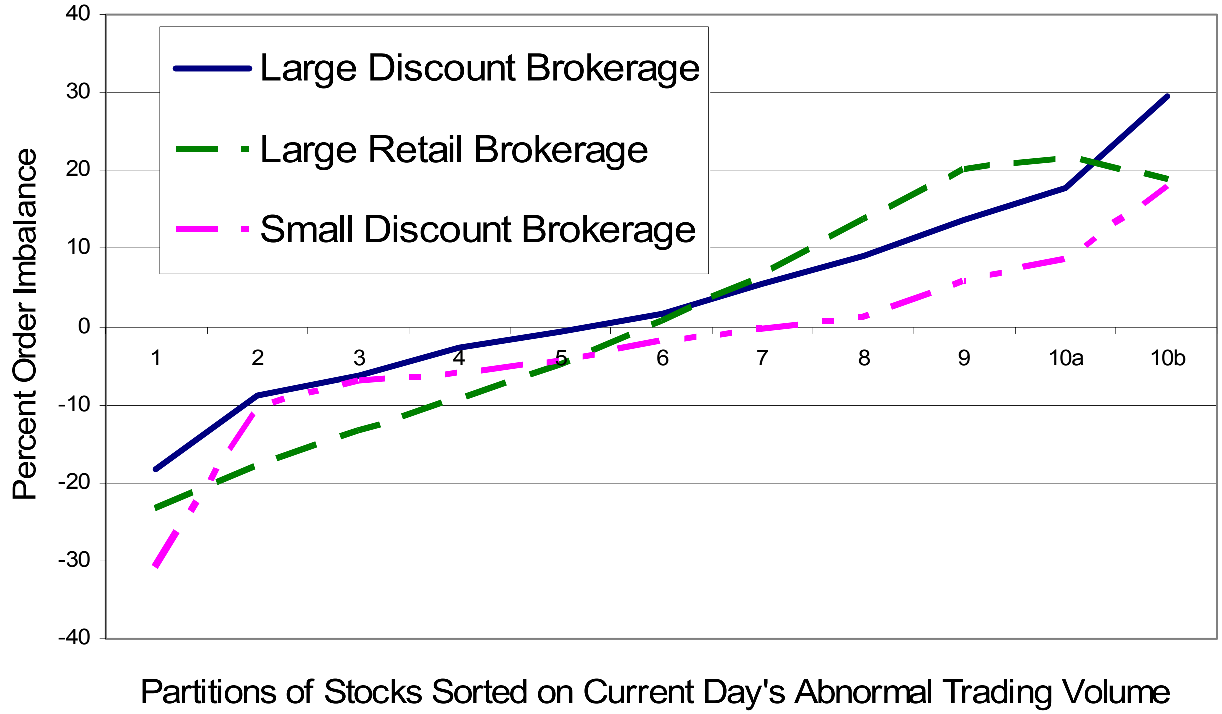

Figure 2b

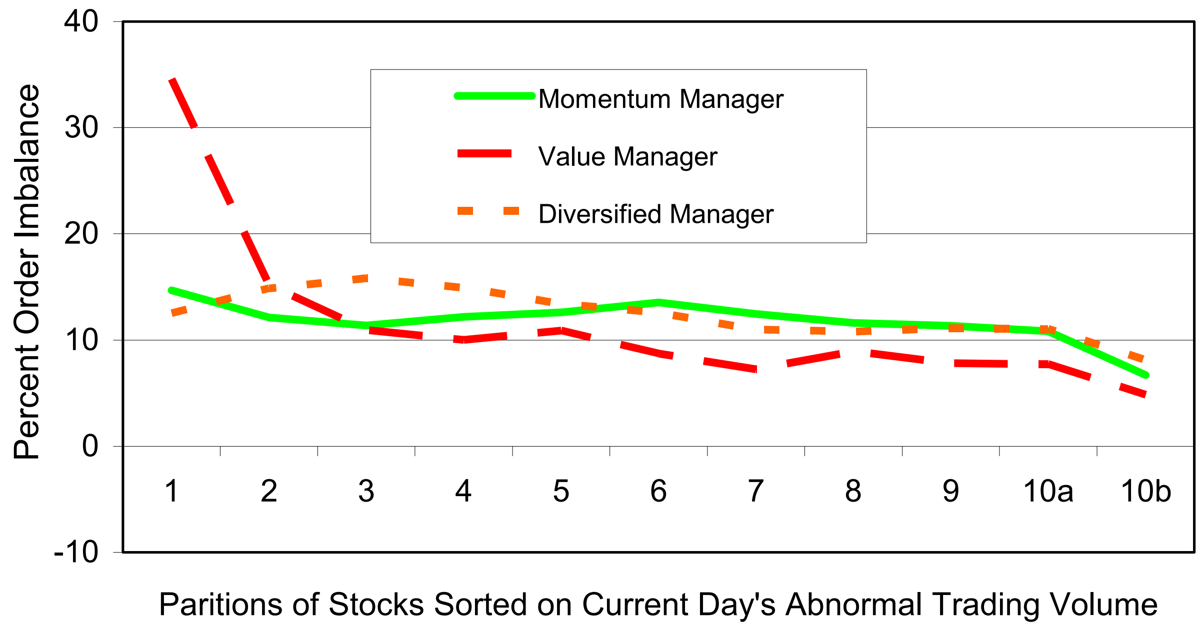

Figure 3: Order imbalance by Number of Trades for Stocks Sorted on the Previous Day's Return

Stocks are sorted daily into deciles on the basis on 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). Figure 3a graphs order imbalances for investors at a large discount brokerage (1991-1996), investors at a large retail brokerage (January 1997 through June 1999), and investors at a small discount brokerage (January 1997 through June 1999). Figure 3b graphs order imbalances for institutional money managers (January 1993 through March 1996) classified 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. The figure depicts the mean for each time-series of daily imbalances for a particular investor group.

Figure 3a

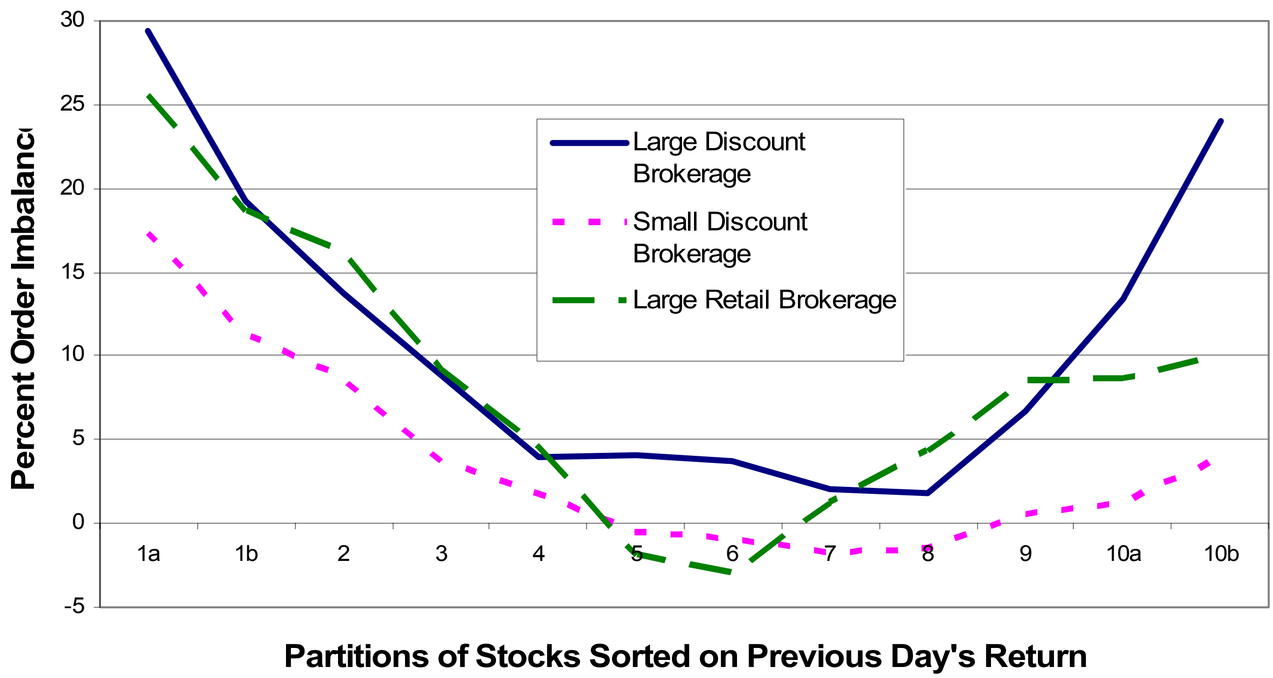

Figure 3b