Do Noise Traders Move Markets?

Brad M. Barber
bmbarber@ucdavis.edu
www.gsm.ucdavis.edu/~bmbarber

Terrance Odean
odean@haas.berkeley.edu
faculty.haas.berkeley.edu/odean

Ning Zhu[1]
nzhu@ucdavis.edu
faculty.gsm.ucdavis.edu/~nzhu

December 2005

Abstract

We study the trading behavior of individual investors using the Trade and Quotes (TAQ) and Institute for the Study of Security Markets (ISSM) transaction data over the period 1983 to 2001. We document three results: (1) Order imbalance based on buyer- and seller-initiated small trades from the TAQ/ISSM data correlate well with the order imbalance based on trades of individual investors from brokerage firm data. This indicates trade size is a reasonable proxy for the trading of individual investors. (2) Order imbalance based on TAQ/ISSM data indicate strong herding by individual investors. Individual investors predominantly buy (sell) the same stocks as each other contemporaneously. Furthermore, they predominantly buy (sell) the same stocks one week (month) as they did the previous week (month). (3) When measured over one year, the imbalance between purchases and sales of each stock by individual investors forecasts cross-sectional stock returns the subsequent year. Stocks heavily bought by individuals one year underperform stocks heavily sold by 4.4 percentage points in the following year. The spread in returns of stocks bought and stocks sold are greater for small stocks and stocks heavily traded by individual investors. Among stocks heavily traded by individual investors, the spread in returns between stocks bought and stocks sold is 13.5 percentage points the following year.

Over shorter periods such as a week or a month, a different pattern emerges. Stocks heavily bought by individual investors one week earn strong returns in the subsequent week, while stocks heavily sold one week earn poor returns in the subsequent week. This pattern persists for a total of three to four weeks and then reverses for the subsequent several weeks. In addition to examining the ability of small trades to forecast returns, we also look at the predictive value of large trades. In striking contrast to our small trade results, we find that stocks heavily purchased with large trades one week earn poor returns in the subsequent week, while stocks heavily sold one week earn strong returns in the subsequent week.

---

[1] Barber and Zhu are at the Graduate School of Management, UC-Davis. Odean is at the Haas School of Business, UC-Berkeley. We thank participants at the BSI-Gamma Foundation Conference for comments. We are extremely grateful to the BSI-Gamma foundation for providing financial support for this research. We thank Shane Shepherd for helpful research assistance. Bob Wood helped us navigate the ISSM data, while Gjergji Cici helped us navigate the TAQ data.

Keywords: noise traders, individual investors, return predictability
JEL classifications: D01, D14, G12, G14

The central question in the debate over market efficiency is whether small noise traders significantly distort asset prices. Three things are necessary for this to happen. First, noise traders must misinterpret available information or trade for non-informational reasons. Second, noise trades must be systematically correlated, that is, noise traders must be net buyers or net sellers of the same stocks; if, instead, noise traders buy and sell randomly, their trades will, on average, cancel, rather than reinforce, each other. Third, there must be limits to the ability of rational, well-informed investors to correct mispricing through arbitrage. If these conditions hold, noise trades will distort asset prices. Furthermore, if, in the long run, asset prices gravitate back towards underlying value, then noise trader buying and selling will predict future asset returns. We test that prediction.

Analyzing tick-by-tick transaction level data for U.S. stock markets from 1983 through 2000, we find that proportion of small trades that are buyer initiated in one year reliably predicts cross-sectional returns the following year. The quintile of stocks most heavily bought by small traders each year subsequently underperforms the quintile most heavily sold by an average of 4.4 percentage points the following year. Focusing on stocks heavily traded by small traders, the difference in cross-sectional returns is more dramatic. The quintile of heavily traded stocks that are most consistently bought by small traders one year subsequently underperforms the quintile of stocks most sold by an average of 13.5 percentage points the following year.

Shleifer and Summers (1990), DeLong, Shleifer, Summers, and Waldman (1990a), DeLong, Shleifer, Summers, and Waldman (1991), and Shleifer and Vishny (1997) argue that noise traders may influence prices even in markets where some investors are well informed, because informed traders face risks that are likely to limit their actions. Suppose, for example, an informed trader considers a stock to be overvalued (i.e., believes that its price exceeds its fundamental value). If there exists a perfect substitute for the stock and transactions costs, including short-selling costs, are low, the informed trader can potentially profit from buying the substitute and selling the overpriced stock. If enough informed traders do this, the relative prices of the overpriced security and its substitute will converge. If, however, information is imperfect, no perfect substitutes exist, or transactions costs are high, the informed trader faces a variety of risks.

Among those risks is the possibility that the informed trader's information is simply incorrect. There is a risk that, although the stock is currently overpriced, unanticipated events increase its value but not that of the substitute. There is the risk that mispricing due to investor sentiment increases as sentiment intensifies rather than subsides. And there is a risk that markets will be illiquid when the informed trades wishes to unwind his position.

An extensive empirical literature explores the limits of arbitrage. For example, Pontiff (1996) finds that large absolute differences in price and net asset value for closed-end funds[2] increase when the fund portfolio is more difficult to replicate, when trading costs are high for the stocks in these portfolios, when these stocks pay dividends, and when interest rates are high. Lamont and Jones (2002) document that stocks with binding short-sale constraints subsequently earn poor returns. Han and Wang (2004) analyze whether upper and lower bounds on the fraction of holdings in any one stock limit institutional arbitrage and contribute to return momentum. Wurgler and Zhuravskaya (2002) find that stocks without close substitutes experience greater price jumps when added to the Standard and Poor's 500 index.

Individual investors play the role of noise traders in equity markets. Many recent papers argue that individual investor trading is often motivated by a variety of psychological heuristics and biases. A combination of mental accounting (Thaler, 1985) and risk seeking in the domain of losses (Kahneman and Tversky, 1979) may lead investors to hold onto losing investments and sell winners.[3] The representativeness heuristic (Tversky and Kahneman, 1974) may lead investors to buy securities with strong

[2] Also see Lee, Shleifer, and Thaler (1991).
[3] Statman and Sherfrin (1985) refer to this behavior as the disposition effect, which has been documented in a variety of contexts by Odean (1998a), Weber and Camerer (1998), Heath, Huddart, and Lang (1999), Genesove and Mayer (2001), Grinblatt and Keloharju (2001), Dhar and Zhu (2002), and others.

recent returns because they view recent return patterns to be representative of the underlying distribution of returns (see DeBondt and Thaler (1987), DeLong, Shleifer, Summers, and Waldman (1990b), DeBondt (1993), and Barberis, Shleifer, and Vishny (1998)). Overconfidence may cause investors to trade too aggressively and, in combination with self-attribution bias, could contribute to momentum in stock returns. (See Kyle and Wang (1997), Odean (1998b), Daniel, Hirshleifer, and Subrahmanyam (1998, 2001), and Gervais and Odean (2001)). Limited attention may constrain the set of stocks investors consider buying (Barber and Odean, 2005) causing purchases to be artificially concentrated in attention grabbing stocks. And the desire to avoid future regret may lead investors to repurchase stocks that have gone down in price since they were previously sold or purchased (Odean, Strahilevitz, and Barber, 2004).

Since individual investors tend to place small trades, their purchases and sales must be correlated if they are to appreciably move markets. Barber, Odean, and Zhu (2005) show that the trading of individual investors at a large discount brokerage (1991-1996) and at a large retail brokerage (1997-1999) is systematically correlated. In any month, the investors at these brokerages tend to buy and sell the same stocks. Furthermore, the monthly imbalance of purchases and sales by these investors (i.e., (purchases – sales)/ (purchases + sales)) is correlated over time. Thus, investors are likely to be net buyers (or net sellers) of the same stocks in subsequent months as they are this month. Jackson (2003) also provides evidence that the trading of individual investors is coordinated using Australian data for the period 1991 to 2002. We extend Barber, Odean, and Zhu's findings by showing that the imbalance of buyer and seller initiated small trades on the New York Stock Exchange (NYSE), the American Stock Exchange (ASE), and Nasdaq are highly correlated with the imbalance of purchases and sales by individual investors at the two brokerages . Establishing that small trades are a reasonable proxy for the trading of individual investors allows us to use eighteen years of trades data to test individual investor herding and to test the effect of this herding on subsequent stock returns.

Other studies have examined the relationship between aggregate individual investor buying and *contemporaneous* returns. Over a two-year period, Goetzmann and

Massa (2003) establish a strong contemporaneous correlation between daily index fund inflows and S&P 500 market returns. Kumar and Lee (2005) demonstrate a correlation in the aggregate buy-sell imbalance of individual investors at a large discount brokerage; these investors tend to move money into or out of the market at the same times as each other. Kumar and Lee find that the buy-sell imbalance of individual investors aggregated across stocks is related to contemporaneous stock returns especially for stocks potentially difficult to arbitrage.

Our paper differs from these papers in two important ways: First – and most importantly, we test the implications of persistent buying (or selling) by individuals for subsequent, rather than contemporaneous, cross-sectional returns. Second, we analyze a much longer and broader sample than that used in prior research. The papers that come closest to ours are Hvidkjaer (2005) and Kaniel, Saar and Titman (2004).

In contemporaneous work, Hvidkjaer,[4] like us, uses TAQ and ISSM data to identify buyer and seller initiated small trades. He measures the difference in turnover rates for buyer and seller initiated small trades over periods of one to 24 months. He then analyses the relationship between signed small trade turnover and subsequent cross-sectional returns. Like us, Hvidkjaer finds that when the small trade imbalances are calculated over a year (as well as shorter and longer periods), those stocks most actively purchased (sold) by individual investors underperform in the following year. Hvidkjaer detects evidence of continued underperformance for up to three years. In addition to demonstrating that stocks heavily bought (sold) by individual investors one year earn negative abnormal returns the following year, we also examine the the ability of individual investor trades over shorter periods to forecast cross-sectional returns.

Kaniel, Saar and Titman (2004) look at short horizon returns subsequent to net buying by individual investors for 1,920 NYSE stocks over a three year period. Kaniel, Saar, and Titman find that stocks heavily bought by individuals one week reliably

[4] Hvidkjaer and the authors of this paper became aware of each other's papers after both papers were written.

outperform the market the following week. No corresponding relationship holds for stocks heavily sold. Jackson (2003) finds a similar relation at a weekly horizon in Australia. Consistent with these papers, we find that stocks heavily bought by individual investors one week tend to outperform those sold that week over the subsequent week and month. Unlike these papers, we document that after one month this pattern reverses and the stocks previously bought underperform those previously sold for the next ten months. Unlike these papers, we also look at the predictive value of large trades. In striking contrast to our small trade results, we find that stocks predominantly purchased with large trades one week underperform those predominantly sold that week during the following week. Finally, with the luxury of a longer time-series of data, we are able to analyze the effect of persistent buying (or selling) over a longer annual horizon. In contrast to these papers, we document that when buy sell imbalances are calculated over an annual horizon stocks underperform, rather than outperform, subsequent to individual investor net buying.[5]

Previous studies demonstrate that individual investors lose money through trading. Odean (1999) and Barber and Odean (2001) report that the stocks that individual investors purchase underperform the stocks they sell.[6] Examining all orders and trades over five years by all individual and institutional investors in Taiwan, Barber, Lee, Liu, and Odean (2005a) find that individual investors lose money through trade before subtracting costs, and that these losses result primarily from aggressive (i.e., liquidity demanding) trades. While the losses of individual investors suggest that their trades might have predictive value, previous studies shed little light on the degree to which these trades will forecast cross-sectional differences in stock returns. Furthermore, the brokerage data analyzed by Odean (1999) and Barber and Odean (2001) documents

[5] Hvidkjaer (2004) uses transactional data to investigate the role of small traders in generating momentum in stock returns.

[6] Some individual investors may have more stock picking skill than their peers. Coval, Hirshleifer, and Shumway (2002) find that some individual investors earn reliably positive returns, at least before trading costs. Ivkovich and Weisbenner (2005) argue individual investors profit on investments close to their home, though Seasholes and Zhu (2005) argue these effects are not robust. Ivkovich, Sialm, and Weisbenner (2005) document that individual investors with concentrated portfolios earn strong returns. Barber, Lee, Liu, and Odean (2005b) find that the most active day traders in Taiwan earn positive profits before costs and that three percent of day traders who were most profitable in the previous six months are reliably profitable in the subsequent month even after costs.

purchases and sales but does not indicate whether trades were initiated by the buyer or seller. Thus, some of the losses of investors documented in previous studies could arise from the limit orders of individual investors being opportunistically picked off by institutional investors.

The principal finding of our study is that measured over both long and short horizons imbalance of small buyer and seller initiated trades forecasts subsequent cross-sectional differences in stock returns.

The rest of our paper is organized as follows. The next section describes our data and empirical methods. Section 2 examines evidence that our measure of the proportion of small trades in each stock that are buyer initiated is highly correlated with the buy sell imbalance of investors at a large discount brokerage and large retail brokerage. Furthermore, the proportion of small trades in each stock that are buyer initiated is highly persistent over time. Section 3 presents our principal results demonstrating that the annual proportion of small trades that are buyer initiated predicts future cross-sectional returns. Section 4 concludes.

1 Data and Methods

Our empirical analyses rely on the combination of tick-by-tick transaction data compiled by the Institute for the Study of Securities Market (ISSM) for the period 1983 to 1992 and New York Stock Exchange (NYSE) from 1993 to 2000. The latter database is commonly referred to as the Trade and Quote (TAQ) database. Together, these databases provide a continuous history of transactions on the NYSE and American Stock Exchange (ASE) from 1983 to 1992. Nasdaq data are available from 1987 to 2000, though Nasdaq data are unavailable in six months during this period.[7] We end our analysis in 2000, since the widespread introduction of decimalization in 2001 created a

[7] Nasdaq data are missing in April and May, 1987, April and July, 1988, and November and December, 1989. In addition to these months, there are an additional 46 trading days with no data for Nasdaq between 1987 and 1991. There are also 146 trading days with no data for NYSE/ASE between 1983 and 1991. We use data posted on the Wharton Research Data Services (WRDS) as of August 2005; we are investigating whether these data are available and hope to include these data in subsequent drafts if possible.

profound shift in the distribution of trade size and likely undermines our ability to identify trades initiated by individuals or institutions.

We identify each trade in these databases as buyer- or seller-initiated following the procedure outlined in Lee and Ready (1991). Specifically, trades are identified as buyer- or seller-initiated using a quote rule and a tick rule. The quote rule identifies trades as buyer-initiated if the trade price is above the midpoint of the most recent bid-ask quote and seller-initiated if the trade price is below the midpoint. The tick rule identifies a trade as buyer-initiated if the trade price is above the last executed trade price and seller-initiated if the trade price is below the last executed trade price.

NYSE/ASE and Nasdaq stocks are handled slightly differently. First, since the NYSE/ASE opens with a call auction that aggregates orders, opening trades on these exchanges are excluded from our analysis; the call auction on open is not a feature of Nasdaq, so opening trades on Nasdaq are included. Second, Ellis, Michaely, and O'Hara (2000) document that the tick rule is superior to the quote rule for Nasdaq trades that execute between the posted bid and ask prices. Thus, we follow their recommendation and use the quote rule for trades that execute at or outside the posted quote and use the tick rule for all other trades that execute within the bid and ask prices. In contrast, for NYSE/ASE stocks, we use the tick rule only for trades that execute at the midpoint of the posted bid and ask price.

In addition to signing trades (i.e., identifying whether a trade is buyer- or seller-initiated), we use trade size as a proxy for individual investor and institutional trades as outlined by Lee and Radhakrishna (2000) and partition trades into five bins based on trade size (T):

1. $T \leq \$5,000$ (Small Trades)
2. $\$5,000 < T \leq \$10,000$
3. $\$10,000 < T \leq \$20,000$
4. $\$20,000 < T \leq \$50,000$
5. $\$50,000 < T$ (Large Trades)

Trades less than \$5,000 (small trades) are used as a proxy for individual investor trades, while trades greater than \$50,000 (large trades) are used as a proxy for institutional trades. Lee and Radhakrishna trace signed trades to orders for 144 NYSE stocks over a three month period in 1990-91 and document that these trade size bins perform well in identifying trades initiated by individual investors and institutions. To account for changes in purchasing power over time, trade size bins are based on 1991 real dollars and adjusted using the consumer price index.

In each month from January 1983 to December 2000, we calculate the proportion of signed trades for a stock that is buyer initiated during the month within each trade size bin. All proportions are weighted by value of trade, though results are similar using the number of trades. In each month, we limit our analysis to stocks with a minimum of ten signed trades within a trade size bin. It is perhaps worth noting that, while on a dollar weighted basis there must be a purchase for every sale, no such adding up constraint exists for buyer and seller initiated trades. In any given period, buyers (or sellers) can initiate the majority of trades.

2 Preliminary Analyses

2.1 Do Small Trades Proxy for Individual Investor Trades?

Several recent empirical studies rely on the assumption that trade size is an effective proxy for identifying the trades of individual questions (see, e.g., Hvidkjaer (2004, 2005), Shanthikumar (2003), Malmendier and Shanthikumar (2004), and Shanthikumar (2005)). To date, the only empirical evidence validating this claim is provided by Lee and Radhakrishna (2000), who analyze a limited sample of 144 NYSE stocks over a three month period in 1990-1991. We externally validate the use of trade size as a proxy for the trading of individual investors over a much wider sample of stocks and a longer time period.

To test the effectiveness of using small trades as a proxy for individual investor trading, we compare the trading patterns for small signed trades in TAQ/ISSM database to trades of individual investors at a large discount broker in the early 1990s and a large retail (i.e., full service) broker in the late 1990s. The large discount broker data contain approximately 1.9 million common stock trades by 78,000 households between January 1991 and November 1996; these data are described extensively in Barber and Odean (2000). The large retail broker data contain approximately 7.2 million common stock trades by over 650,000 investors between January 1997 and June 1999; these data are described extensively in Barber and Odean (2004).

For each of the three trade datasets, we calculate monthly proportion buys for each stock as described above. For each month from January 1991 through November 1996, we calculate the cross-sectional spearman rank correlations between proportion buys for the large discount broker and the proportion buys for each of the five trade size bins in the TAQ/ISSM data. For each month from January 1997 through June 1999, we calculate the correlations between the large retail broker and the TAQ/ISSM data. The mean monthly correlations are presented in Table 1.

The pattern of correlations presented in table 1 provides strong support for the use of small trades as a proxy for individual investor trading. The correlation in proportion buys is greatest for the two smallest trade size bins and gradually declines. In addition, the correlation between trades by individual investors at both the large retail and discount brokers and the TAQ/ISSM large trades are reliably negative. Lee and Radhakrishna (2000) document that large trades are almost exclusively institutional trades. The correlations presented in table 1 indicate the trading patterns of individual investors and institutions are quite different.

In table 2, we present the correlation matrix for monthly proportion buys for each of the five trade size bins using data from the TAQ/ISSM datasets. Consistent with the results in table 1, the mean correlation between proportion buys based on small trades and proportion buys based on large trades is negative, while the correlation of proportion buys for adjacent trade size bins is uniformly positive.

2.2 Are the trades of Individual Investors Coordinated?

Barber, Odean, and Zhu (2005) document strong correlations in individual investor buying and selling activity within a month and over time; investors at the discount and retail brokerages described above tend to buy (and to sell) the same stocks as each other in the same month and in consecutive months; the same is true for investors at the large retail brokerage. Using the same large discount brokerage data, Kumar and Lee (2005) document that investors' movements in and out of the market are also correlated. Kumar and Lee tie these movements to contemporaneous small stock returns.

In this section, we use small trades from TAQ/ISSM to confirm that the trading of individual investors is systematically correlated. We conduct two analyses to verify this. First, we calculate the herding measure described in Lakonishok, Shleifer, and Vishny (1992). Define p_{it} as the proportion of all small (or large) trades in stock i during month t that are purchases (i.e., buyer-initiated). $E[p_{it}]$ is the proportion of all trades that are purchases in month t. The herding measure essentially tests whether the observed distribution of p_{it} is fat-tailed relative to the expected distribution under the null hypothesis that trading decisions are independent and conditional on the overall observed level of buying ($E[p_{it}]$). Specifically, the herding measure for stock i in month t is calculated as:

$$HM_{i,t} = | p_{i,t} - E[p_{i,t}]| - E| p_{i,t} - E[p_{i,t}]|$$

The latter term in this measure – $E| p_{i,t} - E[p_{i,t}]|$ – accounts for the fact that we expect to observe more variation in the proportion of buys in stocks with few trades (See Lakonishok et al. (1992) for details.) If small trades are independent, the herding measure will have a mean of zero.

For both large and small trades, we calculate the mean herding measure in each month from January 1983 through December 2000. For small trades, the mean herding measure is 0.07 and is positive in 214 out of 216 months. For large trades, the mean herding measure is 0.10 and is positive in 196 out of 216 months. For both large and small trades, there is evidence consistent with coordinated trading by individual investors and institutions within the month.

In our second analysis, we analyze the evolution of proportion buys over time by ranking stocks into deciles based on proportion buys in week *t*. We then analyze the mean proportion of trades that are buys in the subsequent two years (104 months) for each of the deciles. If buying and selling is random, we would expect no persistence in the proportion buys across deciles. (Results are qualitatively similar if we form deciles each month rather than each week.)

In Figure 1, we present the week to week evolution of the proportion of buyer initiated trades for deciles sorted on the proportion of buyer initiated trades for small trades and large trades. The figure makes clear that there is strong persistence in the direction of trading based on small trades. In the ranking week, the spread in the proportion buys between the top and bottom decile is 58.1 percentage points for small trades and 55.9 percentage points for large trades. This spread declines slowly for small trades to 23.0, 16.9, 13.7, and 10.4 after 1, 3, 6, and 12 weeks (respectively). In contrast, the spread narrows relatively quickly for large trades to 8.1, 4.7, 3.4, and 2.8 percentage points after 1, 3, 6, and 12 weeks respectively.. This evidence suggests the preferences of individual investors are more persistent than those of institutions.

3 Does Coordinated Trading Predict Returns?

3.1 Portfolio Formation and Descriptive Statistics

The evidence to this point indicates the preferences of individual investors are coordinated and remarkably persistent. We now turn to the focus of our inquiry – does this coordinated trading affect prices? Specifically, we are interested in learning whether the coordinated buying (selling) of individual investors can support prices above (below) levels that would otherwise be justified by the stock fundamentals, thus forecasting subsequent returns. In short, do individual investor preferences influence prices?

To test this hypothesis, we focus first on annual horizons and begin with a very simple approach. In December of each year from 1983 through 2000, we partition stocks into quintiles based on the proportion of signed small trades that are buyer initiated during the year. Using the monthly Center for Research in Security Pricing (CRSP) database, we construct monthly time series of returns on value-weighted and equally-weighted portfolios of stocks in each quintile. Each stock position is held for 12 months (i.e., portfolios are reconstituted in December of each year). We construct analogous portfolios using the proportion of buyer initiated trades based on large trades.

Table 3 present descriptive statistics for the quintiles based on small trades (Panel A) and large trades (Panel B). For quintiles based on the proportion of buyer initiated trades calculated using small trades, stocks bought are larger (mean market cap $1.5 billion) and more heavily traded (mean volume $1.6 billion) than stocks sold (mean market cap of $500 million and mean volume of $368 million). Among stocks predominantly sold, small trades represent a larger proportion of all trades by both value and number. Similar patterns emerge for quintiles base on the proportion of buyer initiated trades calculated using large trades. For all quintiles, small trades represent a high proportion of the total number of trades, while large trades represent a high proportion of the total value of trade.

During the ranking year, with one exception, stocks heavily sold by both individual and institutional investors earn poor returns while stocks heavily bought earn strong returns. This is not at all surprising, since our convention for identifying trades as buyer- or seller-initiated conditions on price moves. Trades that move prices up are considered buyer-initiated, while those that move prices down are seller-initiated. The one exception to this pattern is the value-weighted portfolios based on small trades.

3.2 Univariate Sorts

Our primary annual return results are presented in table 4. Recall that we construct value-weighted and equally-weighted portfolios formed in December of each year and held for 12 months. The most noteworthy result to emerge from this analysis is the spread in returns between stocks heavily bought and stocks heavily sold by individual investors (small trade columns). For value-weighted portfolios, the spread in the raw returns is -37 basis points per month (t=-2.21). This underperformance can be traced largely to the strong performance of stocks heavily sold by individuals. The value-weighted portfolio of stocks heavily sold by individuals beats the market by 38 basis points per month (t=2.58), while the value-weighted portfolio of stocks heavily sold by individuals essentially matches market rates of return.

To determine whether style tilts or factor loadings can explain the return spread, we estimate a four-factor model. We estimate a time-series regression where the dependent variable is the monthly portfolio return less the risk free rate and the four independent variables represent factors related to market, firm size, book-to-market ratio (value/growth), and momentum.[8] Four-factor alphas for the value-weighted portfolios yield a similar return spread of 35 basis points per month (t=2.40), while stocks heavily sold by individual investors continue to earn strong four-factor alphas of 34 basis points (t=2.69). Factors related to market, size, value/growth, and momentum provide little explanatory power for the return spread.

The 35 bps monthly return spread is economically large – translating into a 4.2 percentage points annually. By comparison, during our sample period (1983 to 2000) the mean monthly return on the market, size, value, and momentum factors are 69 bps (t=2.24), -12 bps (t=-0.49), 34 bps (t=1.46), and 92 bps (t=3.11).

The return spread on equally-weighted portfolios is greater than that based on value-weighted portfolios. The raw return spread between stocks heavily bought by individual investors and those sold grows to 44 basis points per month (t=-2.99), while the four-factor alpha grows to 57 basis points per month (t=-4.67). This is not terribly surprising, since the equally-weighted portfolios are more heavily influenced by the

[8] The factor data are from Ken French's data library (mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The construction of these factors is described on the web site.

returns of small stocks; we explore the impact of firm size on our results in greater detail in section 3.4.

The return spread for portfolios formed on the basis of the proportion of buyer initiated large trades is not reliably different from zero. The raw return spread is 5 bps per month, while the four-factor alpha for the long-short portfolio is 0.3 bps per month. Curiously, the middle portfolio (portfolio 3) – i.e., where the proportion of buyer initiated large trades is roughly 0.5 – earns strong returns. We have no ready explanation for this finding.

It is not surprising that large trades, though influential when executed, do not predict future returns. Though large trades are almost exclusively the province of institutions, institutions with superior information almost certainly break up their trades to hide their informational advantage among the trades of smaller, less informed, investors. Thus, the most informative institutional trades are not likely to be the largest trades. Consistent with this portrait of informed trading, Barclay and Warner (1993) provide evidence that medium-sized trades, which they define as trades between 500 and 9,900 shares, have the greatest price impact. Unfortunately, it is difficult to identify smaller institutional trades since they are effectively hiding among the trades of less informed investors. Thus, we are unable to provide a compelling test of the performance of institutional trades using the data presented here.

Campbell, Ramodorai, and Vuolteenaho (2005) develop an algorithm to identify institutional trades that combines signed trades from TAQ and changes in quarterly institutional ownership from Spectrum. Their algorithm provides a promising avenue for developing a better understanding of whether the direction of institutional trades predict future returns.

3.3 Two-Way Sorts

To investigate whether there is any interaction between the proportion buyer initiated trades based on individual and institutional trading, we estimate returns for 25 portfolios based on a five-by-five matrix of stocks sorted independently by (1) the proportion of buyer initiated small trades and (2) the proportion of buyer initiated large trades. The results of this analysis are presented in table 5, where rows represent the quintiles of the proportion of buyer initiated large trades and columns present the quintiles of the proportion of buyer initiated small trades. Of particular interest is the seventh column of numbers (Small Trade B-S), which presents the spread between the returns on portfolios of stocks heavily bought less the returns on stocks heavily sold by small traders for each of the five quintiles of large trade proportion buys. In four of the five large trade quintiles, the return spread is negative. Only among stocks heavily sold by institutions is there no economically meaningful spread between stocks bought and sold by small traders; for the remaining quintiles, the abnormal returns range from 22 to 49 bps per month when we analyze value-weighted returns (Panel A) and 37 to 63 bps per month when we analyze equally-weighted returns (Panel B). The spread in returns between stocks bought and sold by small traders is 34 pbs per month for stocks that are also traded by institutions – very similar to our main results in table 4 that do not condition on the presence of large *and* small trades in the ranking year. Scanning the seventh row of numbers (Large Trade B-S), we again find little consistent evidence that proportion buys based on large trades predict returns.

Of some note, the stocks with the highest proportion of both small and large buyer initiated trades, earn the lowest returns in the subsequent year, with average four-factor alphas of -39 bps per month for the value-weighted portfolio (t = -2.66) and -41 bps per month for the equal-weighted portfolio (t = -3.35). This suggests that buyer initiated trading of a stock by both individual and institutional investors in one year causes an overreaction resulting in underperformance the subsequent year.

3.4 Results by Firm Size

There are several reasons to expect greater return spreads for small stocks (and thus equally-weighted portfolios). First, individual investors tend to tilt their investments toward small stocks relatively more than institutions (Barber and Odean, 2000), while institutional investors tend to prefer the liquidity offered by large stocks (Gompers and

Metrick, 2001). Second, the coordinated trading of individual investors is more likely to impact small stocks, which tend to be less liquid than large stocks. Third, the limits to arbitrage (e.g., transaction costs, price impact, and return volatility) are greater for small stocks. If individual investors support prices above (or depress prices below) levels that would be justified by a firm's fundamental, we would expect the departures from fundamental value to be greatest for small stocks.

For all these reasons, we expect proportion buys based on small trades will provide a better prediction of returns for small, rather than large stocks. To test this hypothesis, we separate our sample into small, medium, and large stocks. Small stocks are defined as stocks with a market cap below the 30th percentile of market cap for NYSE listed stocks, while large stocks are those with market cap above the 70th percentile. Stocks with a market cap between the 30th and 70th percentiles are identified as medium-sized stocks. Size cutoff data are taken from Ken French's data library.

The results of this analysis are presented in table 6. To conserve space, we only present four-factor alphas for value-weighted portfolios. The market-adjusted returns yield a similar pattern. The results for equally-weighted portfolios are somewhat more pronounced, but qualitatively similar. Consistent with our conjecture, the return spread between stocks heavily bought and heavily sold based on small trade proportion buys increases from 29 bps for large stocks (t=1.62) to 33 bps for medium stocks (t=2.68) to 40 bps for small stocks (t=2.81). Consistent with our main results, the direction of large trades are unable to predict returns.

3.5 Results by Small Trade Turnover

We expect the influence of small traders to be greatest when small traders are active. To measure the activity of small traders, we calculate small trade turnover, which we define as the sum of signed small trades divided by average monthly market cap during the ranking year. We then partition stocks into three groups based on small trade turnover. High small trade turnover stocks are those above the 70th percentile of turnover within the year, while low small trade turnover stocks are those below the 30th percentile of turnover. Remaining stocks are placed in the medium trade turnover category. As was done for our main results, we calculate value-weighted portfolio returns separately for each turnover group.

The results of this analysis are presented in table 7. To conserve space, we present only four-factor alphas for value-weighted portfolio returns. Market-adjusted returns and equally-weighted returns yield qualitatively similar results. Sorting on small trade turnover yields a sharp separation in returns. Stocks heavily bought by small traders underperform those sold by 21 bps per month, though the return spread is not reliably different from zero (t=1.28). In contrast, the return spread for mid- and high turnover groups are reliably negative and economically large – 48 bps per month (t=2.50) and 112 bps per month (t=2.58). Again, we find no consistent evidence that stocks heavily bought by large traders earn returns that are substantially different from those for stocks heavily sold by large traders.

3.6 One-Week Calendar Time Return Analysis

Having established that the trading behavior of individual investors in one year forecasts cross-sectional stock returns the following year, we turn our attention to shorter horizons.

First we measure the contemporaneous relationship between the weekly order imbalance of small and large trades and returns the same week, by constructing portfolios as before using weekly rather than annual order imbalance. Specifically, on Wednesday of each week we rank stocks into quintiles based on the proportion buys using small trades. The value-weighted returns on the portfolio are calculated for the contemporaneous week. We obtain a time-series of daily returns for each quintile. We compound the daily returns to obtain a monthly return series. We conduct a similar analysis for portolios constructed based on the proportion buys using large trades.

The results of this analysis are presented in Table 8, Panel A. For both large and small trades, contemporaneous returns are strongly increasing in the proportion of trades that are purchases. Causality could go in either direction or both. That is, an imbalance of purchases (sales) could drive prices up (down) or investors may choose to buy (sell) stocks that are going up (down). We do not attempt to determine causality here. Others who have looked at the relationship between contemporaneous retail investor flows and returns have found evidence of causality in both directions (e.g., Goetzmann and Massa, (2003) and Agnew and Balduzzi (2005)).

Next we examine the ability of one week's order imbalance to forecast the subsequent week's cross-sectional returns. To calibrate the size of the abnormal returns that one might observe from pursuing a strategy of investing in stocks recently bought by small traders, we construct portfolios as before using weekly rather than annual order imbalance. Specifically, on Wednesday of each week we rank stock into quintiles based on the proportion buys using small trades. The value-weighted returns on the portfolio are calculated for the subsequent week (five trading days). Thus, in contrast to our main results, where we rank stocks annually and hold them for one year, in this analysis we rank stock weekly and hold them for one week. Ultimately, we obtain a time-series of daily returns for each quintile. We compound the daily returns to obtain a monthly return series. Again, we conduct a similar analysis for portfolios constructed based on the proportion buys using large trades.

The results of this analysis are presented in Table 8, Panel B. Stocks recently sold by small traders perform poorly (-64 bps per month, t=-5.16), while stocks recently bought by small traders perform well (73 bps per month, t=5.22). Note this return predictability represents a short-run *continuation* rather than reversal of returns; stocks with high weekly proportion buys perform well both in the week of strong buying and the subsequent week. This runs counter to the well-documented presence of short-term reversals in weekly returns.[9]

[9] Gervais, Kaniel, and Minglegrin (2001) find that stocks with unusually high (low) trading volume over a day or a week tend to appreciate (depreciate) over the subsequent month. Weighting stocks equally, we find a positive relationship between turnover and individual investor order imbalance at an annual horizon. In unreported analysis (available from the authors) we find the same relationship at horizons of one week and one month. Barber and Odean (2005) report a strong positive relationship between individual investor order imbalance and abnormal trading volume on a daily basis. Individual investor order imbalance (and its

Portfolios based on the proportion buys using large trades yield precisely the opposite result. Stocks bought by large traders perform poorly in the subsequent week (-36 bps per month, t=-3.96), while those sold perform well (42 bps per month, t=3.57).

We find a positive relationship between the weekly proportion of buyer initiated small trades in a stock and contemporaneous returns. Kaniel, Saar, and Titman (2004) find retail investors to be contrarians over one week horizons, tending to sell more so than buy stocks with strong performance. Like us, they find that stocks bought by individual individual investors one week outperform the subsequent week. They suggest that individual investors profit in the short-run by supplying liquidity to institutional investors whose aggressive trades drive prices away from fundamental value and benefiting when prices bounce back. Barber, Lee, Liu, and Odean (2005) document that individual investors can earn short term profits by supplying liquidity. This story is consistent with the one week reversals we see in stocks bought and sold with large trades. Aggressive large purchases may drive prices temporarily too high while aggressive large sells drive them too low both leading to reversals the subsequent week. However, the provision of immediate liquidity by individual investors does not explain the small trade results presented here (nor is it likely to contribute appreciably to our annual horizon results). Unlike Kaniel, Saar, and Titman's investor sentiment measure, our imbalance measure is unlikely to include liquidity supplying trades since the algorithm we use to sign trades is specifically designed to identify buyer and seller initiated trades. We suspect that, consistent with the noise trader models discussed above, when buying (selling) pressure by individual investors pushes prices up (down) in the current week, continued buying (selling) pressure push prices further up (down) the following week. If so, then prices are being distorted in the direction of individual investor trades and we would expect to find evidence of subsequent reversals.

---

persistence) may contribute to the relationship that Gervais, Kaniel, and Minglegrin document between volume and subsequent returns. If so, we may expect to find at longer horizons relationships between trading volume and subsequent returns that are similar to those we document for order imbalance and subsequent returns.

3.7 Weekly Fama Macbeth Regressions

To explore this issue, we estimate a series of cross-sectional regressions where the dependent variable is weekly returns and the independent variables capture the pattern of past trading activity by small traders. We use weekly, rather than monthly, returns to focus a sharper lens on the impact of past trading on returns at the shorter weekly horizon.

Specifically, we estimate the following cross-sectional regression separately for each week from January 4, 1984, through December 27, 2000:

$$r_t = a + \sum_{w=1}^{4} b_w PB_{t-w} + \sum_{w=5}^{49 by 4} c_{t-w,t-w-3} PB_{t-w,t-w-3} + dBM + eMVE + \sum_{w=1}^{4} f_w r_{t-w} + g r_{t-5,t-52} + \varepsilon$$

where the dependent variable is the percentage log return for a firm in week *t* (r_t).[10] The independent variables of interest include four weekly lags of proportion buys based on small trades (PB_{t-1} to PB_{t-4}) and 12 lags of proportion buys for four-week periods beginning in *t-5* ($PB_{t-5,t-8}$ to $PB_{t-49,t-52}$). As control variables, we include a firm's book to market ratio (BM) and firm size (MVE – log of market value of equity) to control for size and value effects (Fama and French, 1992), four lags of weekly returns (r_{t-1} to r_{t-4}) to control for well-documented short-term reversals (Lehmann (1990) and Jegadeesh (1990)), and the firm return between weeks *t-52* to *t-5* ($r_{t-52,t-5}$) to control for momentum in returns (Jegadeesh and Titman, 1993). The typical week has 1,900 firms included in the cross-sectional regression with a range of 245 firms for the week of March 28, 1984, (before the availability of Nasdaq data) to a maximum of 3,585 in the week of January 12, 2000; 24 weeks are missing between 1984 and 1990 due to missing ISSM data. Statistical inference is based on the mean coefficient estimates and standard error of the mean across 860 weekly regressions.

These results are presented in Figure 2, where we plot the coefficient estimates on lags of proportion buys. As the figure makes clear, consistent with our weekly calendar time results, but in striking contrast to our annual results, recent buying by small traders

[10] Weekly returns are calculated from Wednesday to Wednesday. If Wednesday is a holiday, the first valid trading day following the holiday is used to start or end the week.

is *positively*, rather than negatively, related to current returns. The results at one and two weeks are statistically significant (t=30.06 and t=6.55 for lags of one and two weeks, respectively) and economically large. For example, ceteris paribus, if 60 percent, rather than 50 percent, of the small trades in a stock were buyer-initiated in the past week, the stock would earn a log return that is 18 bps higher during the current week.

Consistent with our annual results, current weekly returns are generally negatively related to buying by small traders in the past five to 52 weeks. The negative effects are most pronounced for weeks t-5 to t-8 and generally shrink in economic and statistical significance as we move to longer lags.

Thus, consistent with noise trader models, the aggressive purchases (sales) of stocks by individual investors coincides with price increases that, eventually, reverse.

4 Conclusion

In theoretical models, trading by not fully rational noise traders can drive prices away from fundamental values. Risk-averse informed traders cannot eliminate mispricing due to limits of arbitrage. When noise traders actively buy, assets become overpriced; when they actively sell, assets become underpriced. Eventually, asset prices are likely to revert towards fundamental values.

In this paper, we analyze eighteen years of tick-by-tick transactional data for U.S stocks. First, we document that small trades provide a reasonable proxy for the trading of individual investors. We externally validate the use of small trades from transactional data by correlating the order imbalance based on small trades to order imbalance based on individual investor trades at a retail and discount brokerage firm during the 1990s. Second, using small trades as a proxy for the trading behavior of individual investors, we find that the buyer initiated (and seller initiated) trades of individual investors are highly correlated; that is, in any given month individual investors systematically buy some stocks and sell others. Furthermore, individual investors tend to buy (or sell) the same stocks one month as they did the previous month.

We report evidence consistent with noise trader models in which the buying (selling) of uninformed investors push prices too high (low) leading to subsequent reversals. We find that weekly imbalances in buyer and seller initiated small trades (trades of less than 5,000 1991 dollars) are correlated with contemporaneous returns and, more importantly, forecast cross-sectional differences in returns for the subsequent week. Stocks that individual investors are buying (selling) during one week have positive (negative) abnormal returns that week and in the subsequent two weeks. These returns then reverse over the next several months.

Calculating imbalances in buyer and seller initiated small trades annually, we document that the quintile of stocks with the highest proportion of buyer initiated small trades underperforms the quintile with the lowest proportion of small trades by 4.4 percentage points over the next year. In contrast, the quintile of stocks with the highest proportion of buyer initiated large trades (trades of over 50,000 1991 dollars) earn returns that are not reliably different from those earned by the quintile with the lowest proportion of small trades. Consistent again with the theory that concentrated buying pressure can drive prices too high, we find that stocks for which both large and small trades were primarily buyer initiated in one year realize negative four-factor alphas of 4.6 percentage points the subsequent year. The ability of small trades to forecast future returns is greatest for the stocks in which one would expect individual investors to exert the most influence. For small capitalization stocks, the quintile of stocks with the highest proportion of buyer initiated small trades underperforms the quintile with the lowest proportion of small trades by 4.8 percentage points over the next year. For those stocks with the highest concentration of individual investor trades, the underperformance over the next year is an impressive 13.5 percentage points. We conclude that noise traders do, indeed, move markets.

References

Agnew, Julie and Pierluigi Balduzzi, 2005, Rebalancing Activity in 401(k) Plans, working paper, Boston College.

Barber, Brad M., Lee, Yi-Tsung, Liu, Yu-Jane and Odean, Terrance, 2005a, Who Loses from Trade? Evidence from Taiwan http://ssrn.com/abstract=529062.

Barber, Brad M., Lee, Yi-Tsung, Liu, Yu-Jane and Odean, Terrance, 2005b, Do Individual Day Traders Make Money? Evidence from Taiwan http://ssrn.com/abstract=529063.

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance*, 2000, 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, 261-292.

Barber, Brad M., and Terrance Odean, 2004, Are individual investors tax savvy? Evidence from retail and discount brokerage accounts, *Journal of Public Economics*, 88, 419-442.

Barber, Brad M. and Odean, Terrance, 2005, All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors http://ssrn.com/abstract=460660

Barber, Brad M., Odean, Terrance and Zhu, Ning, 2005, Systematic Noise http://ssrn.com/abstract=474481.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics*, 49, 307-343.

Barclay, Michael J., and Jerold B. Warner, 1993, Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics*, 34, 281-305.

Campbell, John Y., Ramadorai, Tarun and Vuolteenaho, Tuomo, 2004, Caught On Tape: Predicting Institutional Ownership with Order Flow http://ssrn.com/abstract=519882.

Coval, Joshua D., Hirshleifer, David A. and Shumway, Tyler, 2003, Can Individual Investors Beat the Market? http://ssrn.com/abstract=364000.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and over-reactions, *Journal of Finance*, 53, 1839-1886.

Daniel, Kent D., David Hirshleifer & Avanidhar Subrahmanyam, 2001, Overconfidence, Arbitrage, and Equilibrium Asset Pricing, *The Journal of Finance*, 56, 921-965.

DeBondt, Werner, 1993, Betting on trends: Intuitive forecasts of financial risk and return, *International Journal of Forecasting*, 9, 355-371.

DeBondt, Werner and Richard Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance*, 42, 557-581.

DeLong, J. Bradford, Andre Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990a, Noise Trader Risk in Financial Markets, *Journal of Political Economy*, 98, 703-738.

DeLong, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert J Waldmann, 1990b, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance*, 45, 375-395.

DeLong, J. Bradford, Andrei Shleifer, Lawrence Summers, and Robert J Waldmann, 1991, The survival of noise traders in financial market, *Journal of Business*, 64, 1-20.

Dhar, Ravi and Zhu, Ning, 2005, Up Close and Personal: An Individual Level Analysis of the Disposition Effect, forthcoming, *Management Science*.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara, 2000, The accuracy of trade classification rules: Evidence from Nasdaq, *Journal of Financial and Quantitative Analysis,* 35, 529-551.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance*, 54, 1939-1967.

Gervais, Simon, Ron Kaniel, and Dan H. Minglegrin (2001), The high-volume return premium, *Journal of Finance*, 55, 877-919.

Gervais, Simon, and Terrance Odean, 2001, Learning to be overconfident, *Review of Financial Studies,* 14, 1-27.

Genesove, David, and Chris Mayer, 2001, Nominal loss aversion and seller behavior: Evidence from the housing market, *Quarterly Journal of Economics*, 116, 1233-1260.

Goetzmann, William N., and Massimo Massa, 2003, Index Funds and Stock Market Growth *The Journal of Business*, 76, 1–28.

Gompers, Paul A., and Andrew Metrick, 2001, Institutional Investors and Equity Prices, *Quarterly Journal of Economics*, 116, 229-259.

Grinblatt, Mark and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance*, 56, 589-616.

Han, Bing and Wang, Qinghai, 2004, Institutional Investment Constraints and Stock Prices http://ssrn.com/abstract=628683.

Heath, Chip, Steven Huddart, and Mark Lang. 1999, Psychological Factors and Stock Option Exercise, *Quarterly Journal of Economics*, 114, 601–627.

Hvidkjaer, Soeren, 2004, A Trade-Based Analysis of Momentum, forthcoming, *Review of Financial Studies*.

Hvidkjaer, Soeren, 2005, Small trades and the cross-section of stock returns, working paper, University of Maryland.

Ivkovich, Zoran, Sialm, Clemens and Weisbenner, Scott J., 2005, 1Portfolio Concentration and the Performance of Individual Investors http://ssrn.com/abstract=568156.

Ivkovich, Zoran, and Scott J. Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *Journal of Finance*, 60, 267-306.

Jackson, Andrew, 2003, The Aggregate Behavior of Individual Investors http://ssrn.com/abstract=536942.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance*, 45, 881-898

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance*, 48, 65-91.

Kahneman, Daniel, and Amos Tversky. 1979, Prospect Theory: An Analysis of Decision under Risk, *Econometrica*, 46, 171–185.

Kaniel, Ron, Saar, Gideon and Titman, Sheridan , 2004, Individual Investor Sentiment and Stock Returns http://ssrn.com/abstract=600084.

Kumar, Alok and Lee, Charles M. C., Retail Investor Sentiment and Return Comovements (May 2005). http://ssrn.com/abstract=502843

Kyle, Albert, and F. Albert Wang, 1997, speculation duopoly with agreement to disagree: Can overconfidence survive the market test? *Journal of Finance*, 52, 2073-2090.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1992, The impact of institutional trading on stock prices, *Journal of Financial Economics*, Vol. 32, No. 1, pp. 23-43.

Lamont, Owen A., and Charles M. Jones, 2002, Short-sale constraints and stock returns, *Journal of Financial Economics,* 66, 207-239.

Lee, Charles M. C., and Balkrishna Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, *Journal of Financial Markets,* 3, 83-111.

Lee, Charles M. C., and Mark J. Ready, 1991, Journal of Finance, 46, 733-46

Lee, Charles M.C., Andrei Shleifer, and Richard H. Thaler, 1991, Investor Sentiment and the Closed-End Fund Puzzle, *Journal of Finance*, 46, 75-109.

Lehman, Bruce N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics*, 105, 1-28.

Malmendier, Ulrike and Shanthikumar, Devin M., 2004, Are Investors Naive About Incentives? http://ssrn.com/abstract=601114.

Odean, Terrance, 1998a, Are investors reluctant to realize their losses?, Journal Of Finance, Vol. 53, No. 5, p.1775-1798.

Odean, Terrance, 1998b, Volume, volatility, price, and profit when all traders are above average, *Journal of Finance* 53, 1887-1934.

Odean, Terrance, 1999, Do investors trade too much?, *American Economic Review*, 89, 1279-1298.

Odean, Terrance, Strahilevitz, Michal and Barber, Brad M., 2004, Once Burned, Twice Shy: How Naive Learning and Counterfactuals Affect the Repurchase of Stocks Previously Sold http://ssrn.com/abstract=611267.

Pontiff, Jeff, 1996, Costly Arbitrage: Evidence from Closed End Funds, *Quarterly Journal of Economics*, 111, 1135-1152.

Seasholes, Mark and Ning Zhu, 2005, Is there Information in the Local Choices of Individuals?, working paper, University of California, Davis.

Shanthikumar, Devin M., 2003, Small and Large Trades Around Earnings Announcements: Does Trading Behavior Explain Post-Earnings-Announcement Drift? http://ssrn.com/abstract=449800

Shanthikumar, Devin M., 2005, Small Trader Reactions to Consecutive Earnings Surprises: A Market Test of Behavioral Theory http://ssrn.com/abstract=449882..

Shleifer, Andrei, and Lawrence Summers, 1990, The Noise Trader Approach to Finance, *Journal of Economic Perspectives,* 4, 19-33

Shleifer, Andrei, and Robert Vishny, 1997, The Limits of Arbitrage, *Journal of Finance*, 52, 35-55

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, 777–782.

Thaler, Richard, 1985, Mental accounting and consumer choice, Marketing Science, 4, 199-214.

Tversky, Amos and Daniel Kahnemann, 1974, Judgment under uncertainty: Heuristics and biases, *Science*, 185, 1124-1131.

Weber, Martin, and Colin F. Camerer, 1998, The Disposition Effect in Securities Trading: An Experimental Analysis, *Journal of Economic Behavior & Organization*, 33, 167-184.

Wurgler, Jeffrey and Ekaterina Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *Journal of Business*, 75, 583-608.

Table 1: Mean Monthly Correlation in the Proportion of Trades that are Buyer Initiated across Datasets

The table presents the mean monthly percentage spearman correlation between proportion buys for TAQ/ISSM trades size bins and proportion buys for trades at a large discount broker (Panel A) and a large retail broker (Panel B). The standard deviations and *t*-statistics are based on the monthly time-series of cross-sectional correlations.

In each month, we calculate the proportion of trades for a stock that are buys using three datasets: TAQ/ISSM, trades at a large discount broker (1/91 to 11/96), and trades at a large retail broker (1/97 to 6/99). For the TAQ/ISSM data, proportion buys are based on trades identified as buyer- or seller-initiated within five trade size bins. Small trades are less than $5,000 and large trades are greater than $50,000 (in 1991 dollars).

	TAQ/ISSM Trade Size Bin:				
	Small Trades	**2**	**3**	**4**	**Large Trades**
	Panel A: Large Discount Broker				
Mean Monthly Correlation	55.4	57.7	54.5	42.8	-26.5
Standard Deviation	11.8	11.6	11.4	16.2	15.7
t-statistic	39.6	42.0	40.4	22.3	-14.2
Minimum	18.7	9.0	15.3	-2.9	-64.9
Maximum	78.8	78.2	75.7	72.1	16.3
Percent Positive	100.0	100.0	100.0	98.6	5.6
	Panel B: Large Retail Broker				
Mean Monthly Correlation	42.6	44.1	38.1	22.1	-14.5
Standard Deviation	5.9	5.4	7.0	8.3	4.2
t-statistic	39.8	45.0	29.7	14.6	-18.8
Minimum	30.2	34.6	28.4	10.4	-21.5
Maximum	55.8	56.9	52.0	42.9	-4.5
Percent Positive	100.0	100.0	100.0	100.0	0.0

Table 2: Correlation Matrix in Monthly Proportion of Trades that are Buyer Initiated for Five Trade Size Bins

Cross-sectional spearman rank correlations between trade size bins are calculated each month. The table presents the mean percentage correlation in the proportion of buyer-initiated trades for five trade size bins from January 1983 to December 2000. The proportion of buyer-initiated trades is based on TAQ/ISSM trades identified as buyer- or seller-initiated within five trade size bins. Small trades are less than $5,000 and large trades are greater than $50,000 (in 1991 dollars).

	Trade Size Bin:				
	1 (Small)	2	3	4	5 (Large)
1 (Small)	100.0				
2	66.3	100.0			
3	41.9	58.1	100.0		
4	15.2	30.0	45.5	100.0	
5 (Large)	-7.0	-2.7	6.6	22.3	100.0

Table 3: Descriptive Statistics for Quintiles based on Annual Proportion Buys

Quintiles are formed on the basis of annual proportion buyer-initiated transactions for small trades (Panel A) and large trades (Panel B) from 1983 through 2000. The table presents means across all stock-year observations. Market cap is average month-end market cap in the ranking year. Annual turnover is total CRSP dollar volume during the year scaled by market cap. Mean monthly market-adjusted returns are time series means for portfolios constructed in the ranking year.

	Proportion Buyer-Initiated Quintile				
	1 (Heavily Sold)	**2**	**3**	**4**	**5 (Heavily Bought)**
PANEL A: Small Trade Quintiles					
Stock-Year Observations	17,217	17,230	17,230	17,230	17,223
No. of Trades	6,581	11,176	18,013	28,362	30,874
Value of Trades ($000)	368,064	473,640	668,682	1,088,177	1,664,742
Market Cap ($000)	511,330	606,102	608,347	814,668	1,568,670
Small Trades / All Trades (by No.)	0.481	0.504	0.489	0.458	0.404
Small Trades / All Trades (by Value)	0.156	0.174	0.162	0.141	0.112
Large Trades / All Trades (by No.)	0.095	0.077	0.077	0.083	0.102
Large Trades / All Trades (by Value)	0.486	0.431	0.432	0.452	0.507
Annual Turnover	0.572	0.820	1.136	1.350	1.130
	Proportion of Trades that are Buyer-Initiated by Trade Size:				
Small Trades (< $5,000)	0.345	0.451	0.497	0.538	0.611
2 ($5,000 to $10,000)	0.400	0.467	0.494	0.516	0.554
3 ($10,000 to $20,000)	0.432	0.475	0.490	0.502	0.522
4 ($20,000 to $50,0000)	0.463	0.486	0.490	0.495	0.499
Large Trades (> $50,000)	0.488	0.487	0.482	0.479	0.477
	Mean Monthly Market-Adjusted Returns (%) in Ranking Year:				
Equally-Weighted	-0.723	-0.732	-0.232	0.429	0.753
Value-Weighted (by Market Cap)	0.387	0.075	-0.184	-0.250	0.040
PANEL B: Large Trade Quintiles					
Stock-Year Observations	13,874	13,884	13,885	13,884	13,878
No. of Trades	5,752	15,276	41,198	41,323	20,839
Value of Trades ($000)	118,593	470,229	1,827,672	2,388,146	1,348,882
Market Cap ($000)	183,406	473,435	1,278,538	2,684,752	1,643,844
Small Trades / All Trades (by No.)	0.482	0.389	0.330	0.324	0.401
Small Trades / All Trades (by Value)	0.119	0.075	0.054	0.054	0.084
Large Trades / All Trades (by No.)	0.065	0.099	0.129	0.142	0.100
Large Trades / All Trades (by Value)	0.428	0.513	0.578	0.596	0.515
Annual Turnover	0.848	1.233	1.569	1.273	0.888
	Proportion of Trades that are Buyer-Initiated by Trade Size:				
Small Trades (< $5,000)	0.492	0.507	0.506	0.491	0.478
2 ($5,000 to $10,000)	0.482	0.496	0.500	0.490	0.480
3 ($10,000 to $20,000)	0.470	0.489	0.497	0.493	0.485
4 ($20,000 to $50,0000)	0.459	0.485	0.498	0.502	0.501
Large Trades (> $50,000)	0.317	0.446	0.491	0.530	0.630
	Mean Monthly Market-Adjusted Returns (%) in Ranking Year:				
Equally-Weighted	-0.852	-0.258	0.363	0.845	0.693
Value-Weighted (by Market Cap)	-0.988	-0.790	-0.541	0.294	0.734

Table 4: Mean Monthly Percentage Abnormal Returns and Factor Loadings for Portfolios formed on the basis of Annual Proportion of Buyer-Initiated Trades: 1984 to 2001

Portfolios are formed in December of each year, 1983 to 2000, based on quintiles of proportion buys calculated using small trades or large trades. Portfolios are value-weighted (by market cap) or equally-weighted; each stock is held for 12 months. Market-adjusted returns (Panel A) are the differences between the portfolio return and a value-weighted market index. Four-factor alphas (Panel B) are the intercepts from the following regression: $(R_{pt} - R_{ft}) = \alpha + \beta(R_{mt} - R_{ft}) + sSMB_t + vVMG_t + wWML_t + \varepsilon_t$, where R_{pt} is the monthly portfolio return, R_{ft} is the monthly return on one-month T-Bills, and *SMB*, *VMG*, and *WML* are factors representing size, value/growth, and momentum (winner/loser) tilts. Coefficient estimates from the regression are presented in panels C through F.

	Value-Weighted						Equally-Weighted					
	Return			t-statistic			Return			t-statistic		
Proportion Buyer-Initiated Quintile	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**
	Panel A: Market-Adjusted Returns (%)											
1 (Sold)	0.375	0.021	0.355	2.58	0.13	1.64	0.211	-0.255	0.466	0.99	-1.04	3.84
2	0.154	0.023	0.131	1.46	0.15	0.65	0.293	-0.131	0.424	1.22	-0.56	4.13
3	0.049	0.240	-0.191	0.54	1.72	-1.59	0.116	-0.017	0.133	0.44	-0.08	1.09
4	-0.026	0.095	-0.121	-0.30	1.61	-1.02	-0.082	0.017	-0.099	-0.33	0.11	-0.77
5 (Bought)	0.007	0.071	-0.064	0.09	0.82	-0.55	-0.233	-0.064	-0.169	-1.30	-0.39	-1.71
B-S (5-1)	-0.368	0.051	-0.419	-2.21	0.26	-1.52	-0.444	0.191	-0.635	-2.99	1.72	-3.42
	Panel B: Four-Factor Alphas (%)											
1 (Sold)	0.345	-0.015	0.360	2.69	-0.16	2.33	0.409	-0.017	0.426	2.98	-0.12	5.27
2	-0.021	0.146	-0.167	-0.23	1.32	-1.11	0.572	0.189	0.383	3.85	1.71	4.15
3	0.033	0.409	-0.376	0.39	3.73	-3.50	0.477	0.303	0.174	3.27	3.67	1.46
4	-0.064	0.017	-0.080	-0.92	0.30	-0.84	0.213	0.145	0.068	1.79	2.15	0.70
5 (Bought)	-0.006	-0.011	0.006	-0.07	-0.16	0.06	-0.160	0.075	-0.235	-1.50	0.79	-2.53
B-S (5-1)	-0.350	0.003	-0.354	-2.40	0.03	-1.80	-0.569	0.093	-0.662	-4.67	1.03	-5.02

Table 4 (cont'd)

Proportion Buyer-Initiated Quintile	Value Weighted: Coefficient: Small Trades	Large Trades	Diff.	t-statistic: Small Trades	Large Trades	Diff.	Equally-Weighted: Coefficient: Small Trades	Large Trades	Diff.	t-statistic: Small Trades	Large Trades	Diff.
Panel C: Beta												
1 (Sold)	0.978	0.980	-0.002	30.56	43.14	-0.06	0.863	0.972	-0.109	25.19	26.33	-5.41
2	1.027	1.077	-0.050	45.44	38.89	-1.33	0.989	1.057	-0.068	26.69	38.39	-2.95
3	1.057	1.027	0.030	49.67	37.60	1.13	1.028	1.078	-0.050	28.30	52.33	-1.69
4	1.075	1.011	0.063	61.92	74.82	2.66	1.060	1.087	-0.027	35.67	64.40	-1.11
5 (Bought)	1.051	0.974	0.077	56.66	55.44	3.05	1.051	0.969	0.082	39.42	40.60	3.55
B-S (5-1)	0.073	-0.006	0.080	2.01	-0.21	1.62	0.188	-0.003	0.192	6.20	-0.14	5.83
Panel D: SMB Coefficient												
1 (Sold)	-0.068	0.616	-0.684	-1.71	21.92	-14.37	0.688	0.920	-0.232	16.25	20.14	-9.29
2	0.036	0.450	-0.414	1.30	13.15	-8.89	0.860	0.853	0.007	18.76	25.04	0.25
3	0.179	0.203	-0.023	6.81	5.99	-0.70	0.945	0.743	0.203	21.04	29.13	5.52
4	0.180	-0.113	0.293	8.40	-6.76	9.93	0.934	0.617	0.317	25.40	29.53	10.57
5 (Bought)	-0.055	-0.136	0.080	-2.40	-6.24	2.57	0.695	0.620	0.075	21.09	21.02	2.62
B-S (5-1)	0.013	-0.752	0.765	0.28	-20.07	12.62	0.007	-0.299	0.307	0.19	-10.83	7.54
Panel E: VMG Coefficient												
1 (Sold)	0.281	0.335	-0.054	5.90	9.90	-0.94	0.476	0.325	0.151	9.35	5.92	5.03
2	0.300	0.098	0.202	8.93	2.39	3.61	0.345	0.158	0.187	6.26	3.86	5.45
3	0.048	-0.245	0.293	1.50	-6.04	7.35	0.147	-0.016	0.162	2.71	-0.51	3.67
4	-0.029	-0.005	-0.024	-1.12	-0.25	-0.67	0.075	0.210	-0.135	1.70	8.38	-3.75
5 (Bought)	-0.052	0.126	-0.178	-1.87	4.83	-4.72	0.276	0.339	-0.064	6.95	9.56	-1.85
B-S (5-1)	-0.333	-0.209	-0.124	-6.14	-4.63	-1.70	-0.201	0.014	-0.215	-4.44	0.42	-4.39
Panel F: WML Coefficient												
1 (Sold)	-0.063	0.008	-0.071	-2.22	0.42	-2.09	-0.202	-0.242	0.040	-6.64	-7.39	2.25
2	0.065	-0.172	0.236	3.22	-6.99	7.08	-0.314	-0.342	0.028	-9.57	-14.01	1.36
3	-0.021	-0.089	0.068	-1.11	-3.67	2.86	-0.349	-0.309	-0.041	-10.84	-16.89	-1.55
4	0.019	0.065	-0.046	1.20	5.40	-2.18	-0.276	-0.205	-0.071	-10.49	-13.69	-3.32
5 (Bought)	-0.013	0.046	-0.059	-0.78	2.95	-2.62	-0.132	-0.175	0.044	-5.57	-8.28	2.12
B-S (5-1)	0.050	0.038	0.013	1.56	1.40	0.29	0.070	0.067	0.003	2.60	3.37	0.12

Table 5: Monthly Percentage Abnormal Returns for Portfolios formed from Five-by-Five Partition on Annual Proportion Buyer-Initiated Trades based on Small Trades (columns) and Large Trades (Rows): 1984 to 2001

Portfolios are formed in December of each year, 1983 to 2000, based on independent quintiles of proportion buyer-initiated trades calculated using small trades or large trades. Portfolios are value-weighted (by market cap); each stock is held for 12 months. Four-factor alphas (Panel B) are the intercepts from the time-series regressions of the excess portfolio return on factors related to the market, size, book-to-market (value/growth), and momentum.

	Four-Factor Alphas (%)							***t*-statistics**						
	Small Trade Proportion Buyer-Initiated Quintile							**Small Trade Proportion Buyer-Initiated Quintile**						
Large Trade Proportion Buyer-Initiated Quintile	**1 (Sold)**	**2**	**3**	**4**	**5 (Bought)**	**All Large Trades**	**Small Trade B-S (5-1)**	**1 (Sold)**	**2**	**3**	**4**	**5 (Bought)**	**All Large Trades**	**Small Trade B-S (5-1)**
	Panel A: Value-Weighted Portfolios													
1 (Sold)	-0.058	0.099	-0.088	-0.054	-0.048	-0.036	0.010	-0.37	0.69	-0.55	-0.37	-0.35	-0.41	0.05
2	0.423	-0.003	0.215	-0.064	0.199	0.154	-0.224	2.39	-0.02	1.39	-0.40	1.11	1.43	-0.98
3	0.715	0.306	0.296	0.184	0.274	0.333	-0.440	2.24	1.91	1.79	0.98	1.83	3.09	-1.31
4	0.502	-0.021	-0.092	-0.207	0.118	0.039	-0.384	2.07	-0.16	-0.68	-1.90	1.06	0.68	-1.47
5 (Bought)	0.103	0.023	-0.123	-0.070	-0.386	-0.112	-0.489	0.54	0.14	-0.72	-0.48	-2.66	-1.46	-2.14
All Small Trade	0.339	-0.024	0.032	-0.064	-0.004	n.a.	-0.343	2.61	-0.26	0.37	-0.91	-0.06	n.a.	-2.33
Large Trade B-S (5-1)	0.161	-0.075	-0.035	-0.016	-0.338	-0.076	n.a.	0.64	-0.35	-0.15	-0.08	-1.63	-0.63	n.a.
	Panel B: Equally-Weighted Portfolios													
1 (Sold)	-0.151	0.254	0.070	-0.077	-0.281	-0.029	-0.130	-0.92	1.29	0.34	-0.37	-1.70	-0.19	-0.74
2	0.259	0.165	0.366	0.223	-0.149	0.176	-0.408	1.66	1.14	2.11	1.48	-1.08	1.60	-2.44
3	0.369	0.338	0.538	0.229	-0.126	0.273	-0.495	2.45	2.74	3.94	1.87	-1.03	3.36	-2.70
4	0.222	0.444	0.103	0.122	-0.154	0.129	-0.376	1.78	3.55	0.88	1.13	-1.26	1.85	-2.57
5 (Bought)	0.212	0.409	0.229	-0.037	-0.413	0.059	-0.625	1.60	2.48	1.59	-0.27	-3.35	0.61	-3.92
All Small Trade	0.175	0.333	0.285	0.094	-0.261	n.a.	-0.435	1.52	2.76	2.37	0.96	-2.58	n.a.	-3.90
Large Trade B-S (5-1)	0.363	0.154	0.159	0.040	-0.132	0.088	n.a.	0.96	0.88	0.21	-0.82	0.98	-0.37	n.a.

Table 6: Monthly Percentage Abnormal Returns by Firm Size for Value-Weighted Portfolios formed on the basis of Annual Proportion Buyer-Initiated Trades using Small and Large Trades: 1984 to 2001

Portfolios of small, medium, and large stocks are formed in December of each year, 1983 to 2000, based on quintiles of proportion buyer-initiated trades calculated using small trades or large trades. Small firms are those below the 30th percentile of NYSE market cap, while large firms are those above the 70th percentile. Remaining firms are classified as medium-sized. Portfolios are value-weighted (by market cap); each stock is held for 12 months. Four-factor alphas (Panel B) are the intercepts from the time-series regressions of the excess portfolio return on factors related to the market, size, book-to-market (value/growth), and momentum.

	Four-Factor Alpha (%)			t-statistic		
Proportion Buyer-Initiated Quintile	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**
	Panel A: Small Firms					
1 (Sold)	0.118	-0.038	0.156	0.92	-0.34	1.52
2	0.311	0.091	0.220	2.67	0.77	2.25
3	0.319	0.417	-0.098	2.51	3.24	-0.95
4	0.236	0.195	0.041	1.94	1.72	0.39
5 (Bought)	-0.279	-0.001	-0.278	-2.30	-0.01	-2.65
B-S (5-1)	-0.398	0.036	-0.434	-2.81	0.39	-2.55
	Panel B: Medium Firms					
1 (Sold)	0.218	-0.102	0.321	1.73	-0.90	2.72
2	0.015	-0.021	0.035	0.14	-0.20	0.35
3	0.147	0.239	-0.092	1.59	2.28	-1.09
4	0.067	0.057	0.011	0.70	0.64	0.11
5 (Bought)	-0.110	-0.158	0.048	-0.88	-1.45	0.44
B-S (5-1)	-0.329	-0.056	-0.273	-2.68	-0.46	-1.58
	Panel C: Large Firms					
1 (Sold)	0.341	-0.255	0.596	2.15	-0.98	1.94
2	-0.034	0.291	-0.325	-0.30	1.53	-1.35
3	-0.016	0.459	-0.476	-0.15	3.49	-3.36
4	-0.053	0.023	-0.076	-0.59	0.38	-0.68
5 (Bought)	0.049	0.029	0.020	0.59	0.36	0.18
B-S (5-1)	-0.292	0.284	-0.576	-1.62	1.01	-1.68

Table 7: Percentage Abnormal Returns by Small Trade Turnover for Value-Weighted Portfolios formed on the basis of Annual Proportion Buyer-Initiated Trades using Small and Large Trades: 1984 to 2001

Portfolios of low, mid, and high small trade turnover are formed in December of each year, 1983 to 2000, based on quintiles of proportion buyer-initiated trades calculated using small trades or large trades. Small trade turnover is calculated as the total value of small trades in the ranking year divided by mean monthly market cap. Low small trade turnover firms are those below the 30th percentile within the year, while high small trade turnover firms are those above the 70th percentile within the year. Remaining firms are classified as mid small trade turnover. Portfolios are value-weighted (by market cap); each stock is held for 12 months. Four-factor alphas (Panel B) are the intercepts from the time-series regressions of the excess portfolio return on factors related to the market, size, book-to-market (value/growth), and momentum.

Proportion Buyer-Initiated Quintile	Four-Factor Alpha (%) Small Trades	Four-Factor Alpha (%) Large Trades	Four-Factor Alpha (%) Diff.	t-statistic Small Trades	t-statistic Large Trades	t-statistic Diff.
	High Small Trade Turnover					
1 (Sold)	1.197	0.130	1.067	3.45	0.44	3.09
2	0.895	0.192	0.703	3.01	0.86	2.56
3	0.147	0.595	-0.448	0.65	1.87	-1.52
4	0.649	0.657	-0.008	2.09	2.20	-0.03
5 (Bought)	0.075	0.323	-0.248	0.24	1.16	-0.76
B-S (5-1)	-1.123	0.193	-1.316	-2.58	0.62	-2.51
	Mid Small Trade Turnover					
1 (Sold)	0.500	-0.082	0.581	3.24	-0.73	3.23
2	0.441	-0.004	0.446	2.91	-0.04	2.65
3	0.327	0.404	-0.077	1.91	2.50	-0.45
4	0.134	0.153	-0.019	0.93	1.00	-0.15
5 (Bought)	0.020	0.164	-0.144	0.13	1.01	-0.88
B-S (5-1)	-0.480	0.245	-0.725	-2.50	1.31	-2.87
	Low Small Trade Turnover					
1 (Sold)	0.267	-0.040	0.307	1.83	-0.33	1.79
2	-0.149	0.258	-0.406	-1.45	1.68	-2.12
3	-0.049	0.388	-0.437	-0.42	3.06	-3.17
4	-0.118	-0.025	-0.092	-1.51	-0.36	-0.85
5 (Bought)	0.059	0.024	0.035	0.68	0.28	0.31
B-S (5-1)	-0.208	0.064	-0.272	-1.28	0.44	-1.25

Table 8: Monthly Percentage Abnormal Returns for Value-Weighted Portfolios formed on the basis of Weekly Proportion Buyer-Initiated Trades using Small and Large Trades: February 1983 to December 2000

Portfolios are formed on Wednesday of each week, 1/4/1983 to 12/27/2000, based on quintiles of weekly proportion buyer-initiated trades calculated using small trades or large trades. In Panel A, positions are taken the first day of the ranking period and held for the ranking period (i.e., one week). In Panel B, positions are taken the day after ranking and held for one week (five trading days). The daily returns of portfolios are compounded to yield a monthly return series. Four-factor alphas are the intercepts from the time-series regressions of the monthly excess portfolio return on factors related to the market, size, book-to-market (value/growth), and momentum.

	Monthly Four-Factor Alpha (%)			t-statistic		
Panel A: Contemporaneous Returns						
Proportion Buyer-Initiated Quintile	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**
1 (Sold)	-2.398	-7.398	5.000	-9.79	-38.96	28.26
2	-1.205	-5.718	4.513	-6.57	-29.36	27.03
3	-0.422	-1.091	0.668	-3.37	-11.73	4.46
4	0.413	4.111	-3.698	4.20	31.91	-25.73
5 (Bought)	1.786	8.062	-6.277	10.92	35.87	-27.95
B-S (5-1)	4.184	15.460	-11.277	11.99	39.37	-37.91
Panel B: Subsequent Returns						
Proportion Buyer-Initiated Quintile	**Small Trades**	**Large Trades**	**Diff.**	**Small Trades**	**Large Trades**	**Diff.**
1 (Sold)	-0.637	0.421	-1.057	-5.16	3.57	-6.34
2	-0.160	0.797	-0.958	-1.87	8.06	-7.35
3	0.161	0.276	-0.115	1.70	3.53	-0.88
4	0.427	-0.219	0.646	4.81	-2.79	5.61
5 (Bought)	0.733	-0.362	1.095	5.22	-3.96	7.37
B-S (5-1)	1.370	-0.782	2.152	6.55	-5.54	8.26

Figure 1: The Evolution of the Proportion of Buyer-initiated Trades over Time for Small and Large Trades

Stocks are sorted into deciles based on the proportion of signed trades that are buys in week *0*. The figure traces the evolution of the proportion buyer-initiated trades for each decile over the subsequent 104 weeks. Small trades are less than $5,000 and large trades are greater than $50,000 (in 1991 dollars).

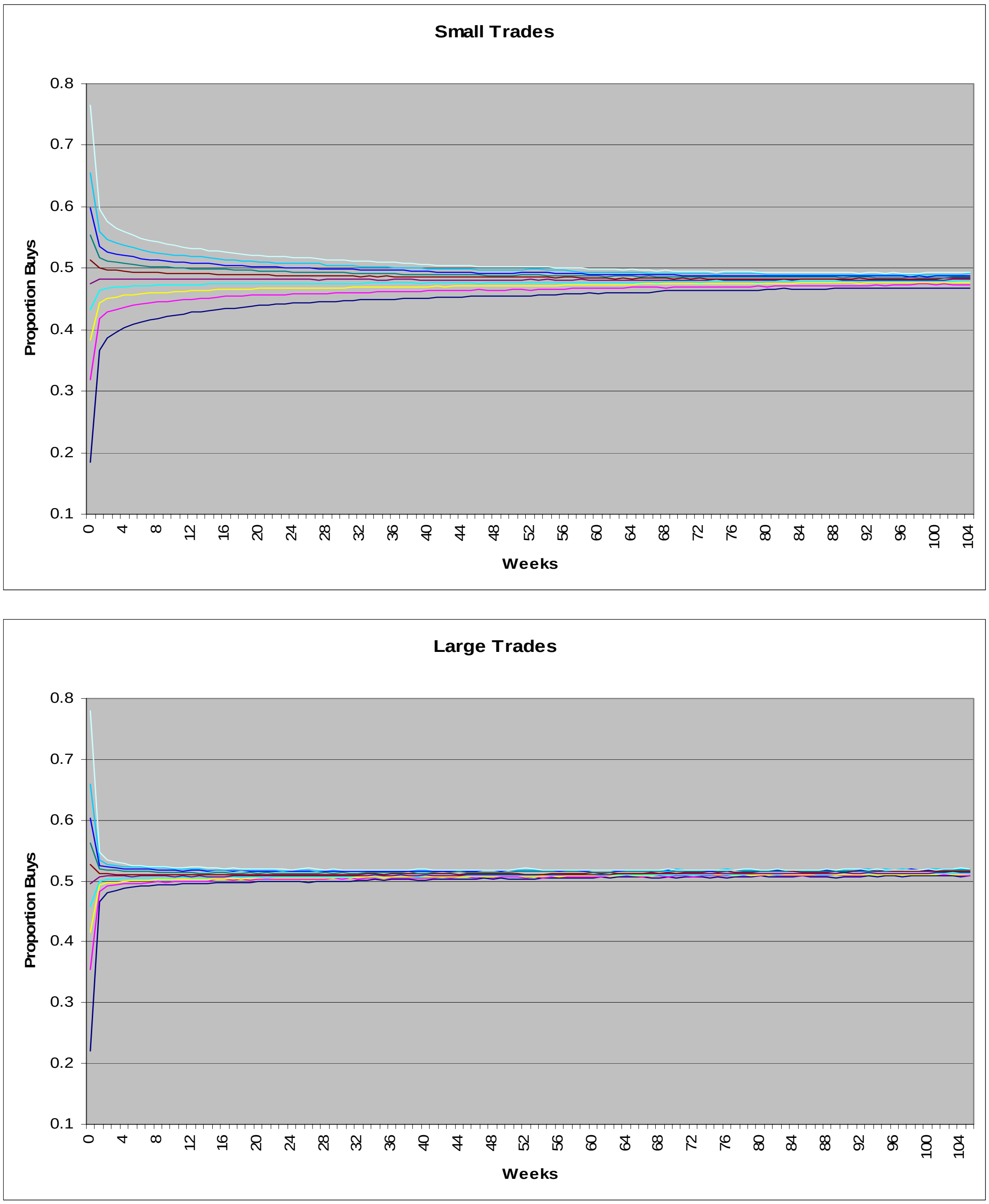


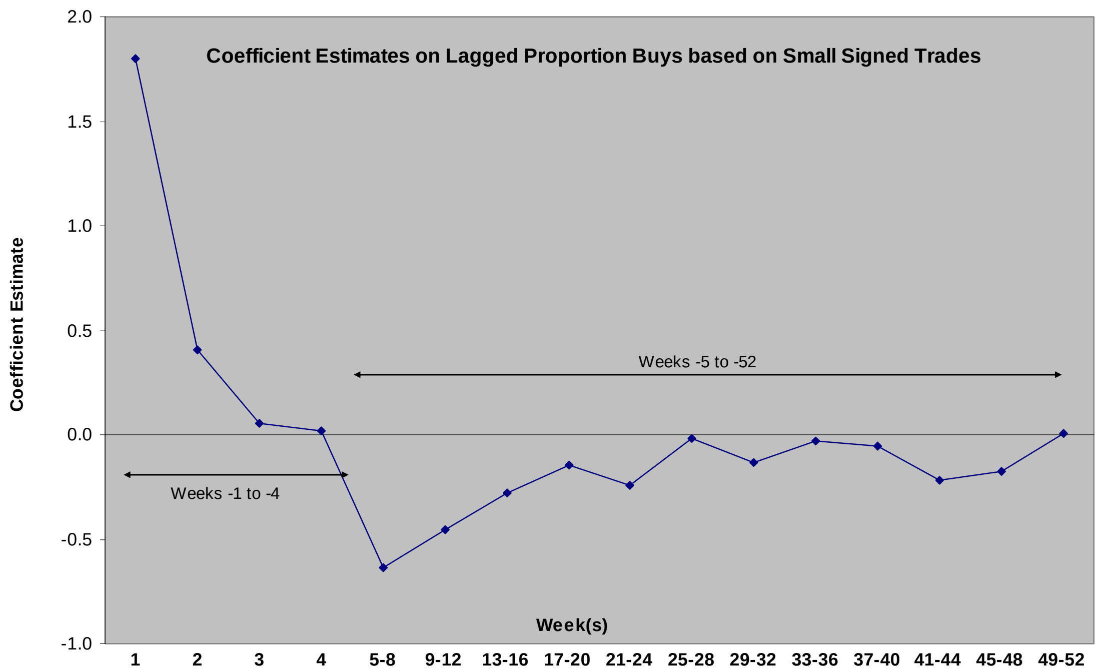
Figure 2: The Effect of Past Small Trade Order Imbalance on Weekly Returns 1984 to 2000

The following cross-sectional regression is estimated in each week from 1/4/84 through 12/27/00:

$$r_t = a + \sum_{w=1}^{4} b_w PB_{t-w} + \sum_{w=5}^{49 by 4} c_{t-w-3,t-w} PB_{t-w-3,t-w} + dBM + eMVE + \sum_{w=1}^{4} f_w r_{t-w} + g r_{t-52,t-5} + \varepsilon \quad ,$$

where r (dependent variable) is the percentage log return for a firm in week t. Independent variables include: *PB*, the proportion buys based on small trades (where lags are included for the past year); *BM*, book-to-market ratio; *MVE*, log of market value of equity; r, lags of weekly returns (percentage log returns for four weeks leading up to week t and the compound return from week t-52 to t-5). Results are based on 860 weekly regressions with a mean of 1,900 observations; 24 weeks are missing due to missing ISSM data.

The figure presents the mean coefficient estimates across weeks on the lagged proportion buy variables. Test statistics are based on the time-series mean and standard deviation of coefficient estimates. Mean coefficient estimates for control variables are presented in the table below the figure.



	1	2	3	4	5-8	9-12	13-16	17-20	21-24	25-28	29-32	33-36	37-40	41-44	45-48	49-52
Coef. Est.	**1.799**	**0.406**	**0.052**	**0.018**	**-0.634**	**-0.457**	**-0.277**	**-0.146**	**-0.242**	**-0.018**	**-0.134**	**-0.030**	**-0.057**	**-0.217**	**-0.176**	**0.008**
t-stat.	**30.06**	**6.55**	**0.85**	**0.29**	**-6.47**	**-5.27**	**-3.16**	**-1.61**	**-2.72**	**-0.21**	**-1.51**	**-0.35**	**-0.67**	**-2.53**	**-2.12**	**0.10**

Coefficient estimates and *t*-statistics for control variables

	BM	MVE	r_{t-1}	r_{t-2}	r_{t-3}	r_{t-4}	$r_{t-52,t-5}$
Coef. Est.	0.052	0.050	-0.112	-0.026	-0.007	0.002	0.005
t-stat.	4.12	3.25	-44.24	-10.96	-3.33	1.14	10.65