Do Retail Trades 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
www.gsm.ucdavis.edu/~nzhu

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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 four results: (1) Order imbalance based on buyer- and seller-initiated small trades from the TAQ/ISSM data correlates 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 indicates 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. For stocks for which it is most difficult to arbitrage mispricings, the spread in returns between stocks bought and stocks sold is 13.1 percentage points the following year. (4) 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.

A central question in the debate over market efficiency is whether investor sentiment influences asset prices. Shleifer and Summers (1990)[2] argue that the demand of some investors "is affected by sentiments not fully justified by fundamental news" and trading by fully rational investors is risky and therefore limited. Thus investor sentiment, as reflected in the retail investor demand, may cause prices to deviate from underlying fundamentals. Our research is motivated by this theory of investor sentiment, though we do not claim to definitively test the theory.

We analyze tick-by-tick transaction level data for U.S. stock markets 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 four 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 that small trades that have been signed using algorithms developed by Lee and Ready (1991) are reasonable proxies for the trades of individual investors. (2) Order imbalance based on TAQ/ISSM data indicates strong herding by individual investors. Individual investors predominantly buy (sell) the same stocks as each other contemporaneously. Furthermore, they predominantly buy (or sell) the same stocks one week (or month) as they did the previous week (or month). (3) Stocks heavily bought by individual investors one week (i.e., stocks for which most small trades that week are buyer initiated) earn strong returns contemporaneously and in the subsequent week, while stocks heavily sold one week earn poor returns contemporaneously and in the subsequent week. This pattern persists for a total of three to four weeks and then reverses for the subsequent several weeks. (4) When measured over one year, small capitalization stocks bought by retail investors have positive contemporaneous returns while medium and large stocks negative contemporaneous returns. For small, medium, and large stocks the imbalance between purchases and sales of retail investors one year 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. For

[2] See also DeLong, Shleifer, Summers, and Waldman (1990a), DeLong, Shleifer, Summers, and Waldman (1991), and Shleifer and Vishny (1997).

stocks for which it is most difficult to arbitrage mispricings, the spread in returns between stocks bought and stocks sold is 13.1 percentage points the following year; for stocks with higher levels of individual investor trading, the spread is 13.5 percentage points the following year. 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, 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. When measured over one year, the imbalance between purchases and sales for large trades has little or no predictive power,

We calculate the percentage of small trades that are buyer initiated. This measure of individual investor trading has distinct advantages over alternative measures as a gauge of investor sentiment. Many recent studies analyze proprietary brokerage account data. Unlike our transactional data, brokerage account records allow researchers to definitively identify trades as retail. However, many retail account databases do not distinguish between executed market and limit orders. We believe that market orders are a better measure of investor sentiment than limit orders because whether or not a limit order is executed depends upon the activities of others. Suppose, for example, that in a particular week, individual investors place an equal number of buy and sell limit orders for a stock, but institutional investors only execute against the buy orders. The heavy buy imbalance of executed individual investor limit orders and the resulting change in investor holdings would, in this case, reflect the beliefs and preferences of the institutions not individuals. Changes in holdings do not provide the information we need about who initiates the trades leading to holdings changes. Furthermore, our transactional data allows us to look at a much longer time period than we could analyze with existing individual account level databases. Previous papers have also analyzed quarterly institutional holdings data such as mutual fund holdings (e.g., Grinblatt and Titman (1989) and Wermers (1999)) and 13F filings data (e.g., Gompers and Mettrick (2001). If the holdings of individual investors are the complement to institutional holdings, one might ask what advantages our data have over institutional holdings data. There are several reasons why our data are better suited to test investor sentiment theories of finance than are quarterly institutional holdings. 1) We are interested in the influence of small investor initiated trades on subsequent cross-sectional returns. Investor holdings can change as a result of both aggressive trades (e.g, market orders) and passive trades (e.g, limit orders). As discussed above, we believe that the distinction between executed market and limit orders is important when measuring investor sentiment.[3] 2) The holdings of investors who place small trades are not the simple complement of reported institutional holdings. Some institutional investors don't file 13Fs but, more importantly, some wealthy individual investors are unlikely to trade like typical retail individual investors. Wolff (2004) reports that over one-third of stock ownership-including direct ownership of shares and indirect ownership through mutual funds, trusts, and retirement accounts-of U.S. households is concentrated in the wealthiest one percent of households. Thus, a large portion of non-institutional holdings are owned by extremely wealthy individuals whose trading is not likely to be driven by the same considerations that motivate the small traders who interest us. 3) Our methodology enables us to examine the relationship between investor trading and subsequent returns over short horizons such as a week. Short horizons cannot be studied with quarterly data.[4]

The rest of our paper is organized as follows. The next section discusses related theoretical and empirical work. Section 2 describes our data and empirical methods. Section 3 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 4 presents our principal results demonstrating that the proportion of small trades that are

[3] 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.

[4] One additional disadvantange of 13F data pointed out by Hvidkjaer (2006) is that it does not include institutional short positions. Thus, if a hedge fund enters into a short position through trades with only institutional investor, this will increase institutional holdings as reported on 13F reports, while if a hedge fund enters into a short position through trades with only individual investors, this will not affect institutional holdings as reported on 13F reports.

buyer initiated predicts future cross-sectional returns at weekly and annual horizons. Section 5 discusses an alternative explanation for our results and Section 6 concludes.

1 Theory and Prior Evidence

Investor sentiment is generally attributed to individual, retail investors (see, for example, Lee, Shleifer, and Thaler (1991)). Since individual investors tend to place small trades, their purchases and sales must be correlated if they are to appreciably affect prices. 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.[5] 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 in the current month. Analyzing Australian data for the period 1991 to 2002, Jackson (2003) also provides evidence that the trading of individual investors is coordinated. 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.

[5] 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 (see Statman and Sherfrin (1985), Odean (1998a), Weber and Camerer (1998), Heath, Huddart, and Lang (1999), Genesove and Mayer (2001), Grinblatt and Keloharju (2001), Dhar and Zhu (2006).The representativeness heuristic (Tversky and Kahneman, 1974) may lead investors to buy securities with strong recent 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) thus concentrating purchases in attention grabbing stocks. And anticipated regret may dissuade investors from purchasing stocks that have risen since they were previously sold or purchased (Odean, Strahilevitz, and Barber, 2004).

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 (2006) 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 for all 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 (2006), Jackson (2003), Dorn, Huberman, and Sengmueller, and Kaniel, Saar and Titman (2006).

In contemporaneous work, Hvidkjaer,[6] 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 ability of individual investor trades over shorter periods to forecast cross-sectional returns.[7]

[6] Hvidkjaer and the authors of this paper became aware of each other's papers after both papers were written.
[7] A note jointly written by Soeren Hvidkjaer and ourselves reconciling methodological differences in this paper and Hvidkjaer (2006) is available at http://faculty.haas.berkeley.edu/odean/reconciliation.pdf .

Jackson (2003) examines Australian brokerage trading records from 1991 through 2001 and finds that net buying is persistent from one week to the next and that net buying one week is followed by positive returns the following week.

Kaniel, Saar and Titman (2006) look at short horizon returns subsequent to net buying by individual investors for 1,920 NYSE stocks from 2000 through 2003. They find that stocks heavily bought by individuals one week reliably outperform the market the following week. Kaniel, Saar and Titman (2006) propose that risk-averse individual investors provide liquidity to institutions that demand immediacy. Thus prices fall as institutions sell to individuals one week and rebound the next.

While Kaniel, Saar, and Titman (2006) and we examine measures of individual investor buying intensity, the data measured differ in key respects. 1) Kaniel, Saar, and Titman (2006) examine only trades directed to the NYSE. Discount brokerages catering to self-directed individual investors send few, if any, trades to the NYSE.[8] Thus Kaniel, Saar, and Titman (2006) see very few trades from discount or deep discount brokerages. We look at all NYSE, ASE, and Nasdaq trades, thus our trading measure includes trades by self-directed individuals. 2) Kaniel, Saar, and Titman's (2006) measure includes executed limit orders. Our measure is designed to exclude limit orders. 3) Kaniel, Saar, and Titman (2006) look only at NYSE listed stocks. We include ASE and Nasdaq stocks. Thus, we look at many more small firms than do Kaniel, Saar, and Titman's (2006) and, as discussed in Section 4, we find substantially different return patterns for large and small firms.

Our empirical findings also differ from those of Kaniel, Saar, and Titman (2006) in critical ways. 1) Our buying intensity measure is positively correlated with weekly contemporaneous returns—what one expects from market orders. Kaniel, Saar, and Titman's buying intensity measure is negatively correlated with daily and weekly

[8] In SEC Rule 606 reports for the first quarter of 2006, Ameritrade, E*Trade, Scottrade, and TD Waterhouse report sending less than one percent of orders for NYSE listed stocks to the NYSE. Schwab reports seven percent.

contemporaneous returns—what one expects from limit orders. 2) Our weekly buying intensity measure is positively correlated with returns over the following two week's and negatively correlated with returns at the fifth week and beyond. This is consistent with the investor sentiment theory that we test. Kaniel, Saar, and Titman's (2006) buying intensity measure is also correlated with the following week's return. However, they do not report the same reversal that we find at the fifth week nor does their story predict such a reversal.

Dorn, Huberman, and Sengmueller (2006) examine trading records for 37,000 investors with accounts at a German discount brokerage. They document correlated trading by these investors at daily, weekly, monthly, and quarterly horizons. Weekly net limit order purchases correlate negatively with contemporaneous returns and positively with returns the following week. Weekly net market order purchases correlate positively with contemporaneous returns and positively with returns the following week.

Andrade, Chang, and Seasholes (2006) examine changes in margin holdings by investors—primarily individual investors—on the Taiwan Stock Exchange. They find that weekly changes in (long) margin holdings correlate positively with contemporaneous returns and negatively with returns over the subsequent ten weeks.

Unlike Jackson (2003), Andrade, Chang, and Seasholes (2006), Dorn, Huberman, and Sengmueller (2006), and Kaniel, Saar, and Titman (2006), 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 weekly results, we document that when the percentage of trades that are buyer initiated is calculated over an annual horizon stocks underperform, rather than outperform, subsequent to individual investor net buying.[9]

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.[10] Examining all orders and trades over five years by all individual and institutional investors in Taiwan, Barber, Lee, Liu, and Odean (2007) 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) identify purchases and sales, but (importantly) 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, the imbalance of small buyer and seller initiated trades forecasts subsequent cross-sectional differences in stock returns.

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

[10] 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 following month even after costs.

2 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.[11] We end our analysis in 2000, since the widespread introduction of decimalization in 2001, together with growing use of computerized trading algorithms to break up institutional trades, created a 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

[11] 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.

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 ≤ $5,000 (Small Trades)
2. $5,000 < T ≤ $10,000
3. $10,000 < T ≤ $20,000
4. $20,000 < T ≤ $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 week (month or year), from January 1983 to December 2000, we calculate the proportion of signed trades for a stock that is buyer initiated during the week (month or year) within each trade size bin. All proportions are weighted by value of trade, though results are similar using the number of trades. In each week (month or year), 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.

3 Preliminary Analyses

3.1 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 investors (see, e.g., Hvidkjaer (2004, 2006), 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 combined with the signing algorithms developed by Lee and Ready (1991) 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 signed 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 the 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. These mean monthly correlations are presented in Table 1.

The pattern of correlations presented in Table 1, Panels A and B, 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, Panels A and B, indicate the trading patterns of individual investors and institutions are quite different.

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

3.2 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 (2006) 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 7 percent and is positive in 214 out of 216 months. This measure of herding is in the same ballpark as the monthly herding measures of 6.8 percent to 12.8 percent estimated for individual investors by Barber, Odean, and Zhu (2005). For large trades, the mean herding measure we estimate is 10 percent and is positive in 196 out of 216 months. Wermers (1999) uses quarterly mutual fund holding data to calculate quarterly herding measures ranging from a low of 1.9 percent to a high of 3.4 percent. Lakonishok, Shleifer, and Vishny (1992) use quarterly pension fund holdings data to calculate a quarterly herding measure of 2.7 percent for the pension funds that they analyze. Thus, our estimate of institutional herding is triple that of previous studies. There are three possible reasons why our estimates of institutional herding are larger than previous estimates. First, we are analyzing herding at a monthly horizon rather than a quarterly horizon. Second, we are analyzing only the initiator of the trade. Third, we are estimating herding for only the largest trade size bin. Institutions that rely on large trades may herd more than all institutions in aggregate. For both large and small trades, we find evidence of coordinated trading within the month.

In our second analysis, we analyze the evolution of proportion buys over time by ranking stocks into deciles based on the proportion buys in week t. We then analyze the mean proportion of trades that are buys in the subsequent 104 weeks 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 trading preferences of individual investors are more persistent than those of institutions.[12]

4 Does Coordinated Trading Predict Returns?

4.1 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)

[12] We observe buyer and seller initiated trades, not actual preferences. In response to a change in preference for some stocks, institutions, as a group, may simply execute their trades more quickly than individuals even though their preferences are no less persistent than those of individuals.

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 following the ranking year (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 2 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.

4.2 Univariate Sorts

Our primary annual return results are presented in Table 3. 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 bought 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.[13] 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.[14]

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

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[13] 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.

[14] In auxiliary analysis, we estimate monthly cross-sectional regressions where the proportion buys from the retail datasets is the dependent variable and proportion buyer-initiated trades from the TAQ trade size bins yield five independent variables. We use the mean results from these regressions to calculate predicted retail order imbalance in each year by applying the mean coefficient estimates from this regression to the annual proportion buyer-initiated trades in each of the five TAQ/ISSM trade size bins for our entire sample period (1983 to 2000). Finally, stocks are ranked based on predicted retail order imbalance in each year. We construct portfolios based on quintiles of predicted retail order imbalance and analyze the returns in the year following ranking. The results are qualitatively similar to, but somewhat weaker, than the results presented in Table 3. This loss of forecasting power may be due to noisy forecasts of retail order imbalance or it may be that because retail order imbalances include executed limit orders while signed small trades focus on market orders, thus providing a better measure of investor sentiment. In additional auxiliary analyis, we rank stocks into quartiles based on the number of months in the sorting year in which the percentage of small signed trades that are purchases is over 50%. We construct portfolios based on these persistence quartiles and analyze the returns in the year following ranking. Results for the monthly persistence measure are qualitatively similar to the percentage buy results presented in Table 3, i.e., the portfolio of stocks with the fewest buy months underperforms the portfolio of stocks with the most buy months in the year following the ranking; monthly persistence results are somewhat stronger than our reported results for equally weighed portfolios and somewhat weaker for value-weighted portfolios.

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 heavily reflect the returns of small stocks which individual investors are more likely to influence.

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.

4.3 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 4, 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 (Panel A, column 7, row 6)–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 the 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.

4.4 Results by Idiosyncratic Risk

Our story predicts stronger price reversals in stocks with more limited arbitrage opportunities. One measure of the limits of arbitrage is the extent to which a stock has readily available substitutes. Several papers (Wurgler and Zhuravskaya (2003), Ali, Hwang, and Trombley (2003), Mendenhall (2004), Mushruwala, Rajgopal, and Shevlin (2006), and Pontiff (2006) among others) argue that stocks with high levels of idiosyncratic risk are more difficult to arbitrage. While one can develop more refined measures (e.g., by searching across all stocks for close substitutes), the prior work in this area documents that a simple measure of idiosyncratic risk is highly correlated with more sophisticated measures. Consequently, we use the standard deviation of the monthly residual from a time-series regression of the firm excess returns on the market excess returns over the 48 months preceding the end of our ranking period as our measure of idiosyncratic risk. (Results are similar if we use the monthly residual from the Fama-French three-factor model.) We then separately analyze return patterns for stocks in bottom 30%, middle 40%, and top 30% based on this measure of idiosyncratic risk.

These results are presented in Table 6 of the paper. 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 idiosyncratic risk yields a sharp separation in returns. We find strong evidence that stocks with higher idiosyncratic risk have stronger reversals; stocks in the top 30 percent of our measure of idiosyncratic risk yield a return spread of -110 bps per month (t=-2.64), while stocks in the middle 40 and bottom 30 percent yield return spreads of only -38 bps per months (t=-1.44) and -29 bps per month (t=-1.56).

4.5 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. Low turnover 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.

4.6 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 a 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.[15,16]

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[15] Stocks with many buyer-initiated trades in period t are more likely to have an end-of-period price posted at the ask, while stocks with many seller-initiated trades in period t are more likely to have an end-of-period price posted at the bid. Thus, absent other effects, we would expect stocks heavily bought to have negative returns in period t+1 if the closing price at period t+1 is equally likely to be a bid or ask, while (for similar reasons) stocks heavily sold would have positive returns in period t+1. The size of these reversals would depend on the size of the percentage spread. This microstructure effect works against our finding that stocks with more buyer (seller) initiated small trades one week have strong (weak) returns the next, but could contriubute to the opposite pattern for large trades.

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 (2006) 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 investor sentiment 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

[16] 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. We find a positive relationship between turnover and individual investor order imbalance at an annual horizon (Table 2). 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 persistence) may contribute to the relationship that Gervais, Kaniel, and Minglegrin (2001) document between volume and subsequent returns.

so, then prices are being distorted in the direction of individual investor trades and we would expect to find evidence of subsequent reversals.

4.7 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. 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).[17] 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, i.e., 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

[17] 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 investor sentiment models, the aggressive purchases (sales) of stocks by individual investors coincides with price increases (decreases) that, eventually, reverse.

5 An Alternative Explanation

An alternative explanation for our annual results is offered by an anonymous referee. In this story, individuals provide liquidity to institutions. Institutions begin selling stocks that they believe to be overvalued. The overvaluation that institutions perceive could be driven by changes in firms' fundamental values. Individuals notice falling prices for some stocks and purchase stocks for prices that appear to them to be below intrinsic values. Individuals then wind up holding overvalued stocks, and the long-run returns of the stocks they purchase are negative, reflecting the information of the institutions that sold them the stocks.

This story is similar to that proposed by Kaniel, Saar and Titman (2006) in which individual investors provide liquidity to institutional investors. However, in Kaniel, Saar, and Titman (2006) institutions demand liquidity over periods of days, not months or years. In this alternative story, market inefficiencies do not result from the biases of individual investors but, rather, from the inability of institutional investors to immediately identify and correct mispricings. Once recognized, mispricings can require one to two years to correct. This story predicts that prices fall as individual investors buy. The theory we are testing predicts prices rise as individual investors buy. Consistent with our theory, we find that, at weekly horizons, the proportion of small trades that are buyer initiated and contemporaneous returns are positively correlated (Table 8, Panel A).

At annual horizons, the evidence is not as straight-forward. When stocks are sorted into quintiles on the basis of the proportion of small trades that are buyer initiated, equally-weighted portfolios of stocks in quintiles with more buyer initated trades have higher returns in the sorting year than do portfolios with more seller initated trades (Table 2, bottom of Panel A). However, this pattern does not hold when portfolios are weighted by each firm's market capitalization; now quintiles with more buyer initiated trades have lower returns in the sorting year.

Differences in the behavior of equally-weighted and value-weighted portfolios often result from differences in the behavior of large and small firms. To test for firm size differences, and conduct the following analyses. On each <u>day</u>, we rank stocks into quintiles based on the daily proportion of signed small trades that are buyer initiated (requiring a minimum of 10 trades). We then calculate the returns for these stocks during the ranking day. For each quintile, the mean abnormal return is calculated weighted by the market cap of each firm. We separately analyze small, medium, and large firms. We repeat the same analysis, basing our rankings on <u>monthly</u> and annual rather than daily order imbalance. Results for the extreme quintiles are reported in Table 9.

At a daily horizon, the returns are consistent with the direction of order imbalance and the relation is stronger for small than for medium and large firms. At a monthly horizon, the pattern of returns small firm returns is still consistent with order imbalance. But medium and large firm returns are negative in months when individuals are net buyers and positive when they are net sellers. We know from prior work (e.g., Odean, 1999), that the buying and selling decisions of individual investors are quite sensitive to past returns. Measuring returns and individual investor trading imbalance during the same month (or year) conflates the contemporaneous impact of trading on returns with the impact of recent returns on individual investor trading decisions.

To better understand the timing of these returns within a month, we plot cumulative abnormal returns around the ranking day, we separate our sample into small, medium, and large stocks and sort stocks each day into quintiles on the proportion of small trades that are buyer initiated. On each event day, we calculate the market-adjusted return for each stock (firm return less value-weighted market return). Weighted mean market-adjusted returns are calculated on each event day, where market capitalization from the beginning of the analysis period is used to weight returns on all event days. Cumulative market-adjusted returns (CARs) are the sum of daily mean market-adjusted returns. In Figure 3, Panel A, daily CARs are plotted separately for small, medium, and large firms..

The patterns of returns leading up to the ranking day are consistent across the different size partitions. Stocks with a high proportion of sells on the ranking day experience strong returns prior to the ranking day, while stocks with a high proportion of buys on the ranking day experience poor prior returns. Importantly, the pattern of returns leading up to the ranking day is stronger than the returns on the ranking day for medium and large stocks. In contrast, for small stocks where the impact of these small trades are (relatively) large, the pattern of returns leading up to the ranking day are weaker than the returns on the ranking day.

These daily patterns of returns likely explain the apparently inconsistent monthly returns that we observe in Table 9. For example, large firms with a large proportion of buys earn negative returns of 79 bps in the ranking month. This is consistent with the daily pattern that we observe in Figure 3, Panel A, where stocks with a high proportion of buys earn poor returns in the days prior to ranking. For big firms, where the price impact of small trades is relatively small, it is almost certainly the case that the negative returns preceding individual investor net buying are the predominant reason we observe negative returns in months with a high proportion of buyer-initiated small trades.

In the main analyses in this paper, we analyze returns based on ranking periods of one year. During the ranking year, equally-weighted portfolios earn returns consistent with the direction of order imbalance, but value-weighted portfolios do not (see Table 2, bottom of panel A). The difference in value-weighted and equally-weighted results suggest different patterns for small and large firms. In auxiliary analyses, we confirm small firms earn returns during the ranking year that are consistent with the direction of trades, medium and big firms do not.[18] Again we believe the most likely explanation is the pattern of returns leading up to these trades within the year.

Within a sorting year, an average of six months of returns will precede a trade. In Figure 3, Panel B, we plot monthly CARs for monthly order imbalance quintiles. For small firms, over the six months preceding the sorting month, stocks predominantly bought during the sorting month outperform those predominantly sold; only in the two months leading up to the sorting month does this pattern reverse. For medium and large firms, during the six months preceding the sorting month, stocks predominantly bought in the sorting month underperform those predominantly sold; on average individual investors are net buyers of stocks with significant recent losses and net sellers of stocks with significant recent gains. The negative relationship we observe between annual returns for medium and large stocks and net individual buying during the same year, appears to be driven by returns in months leading up to individual investor trading. Thus we are able to reconcile the annual contemporaneous returns of medium and large stocks with our theory; however, these returns are also consistent with the alternative explanation.

Imbalances in buyer and seller initiated trades move prices. The impact is greatest for small firms which are likely to be more difficult to arbitrage and to have greater individual investor trading turnover. The negative relationship we document between the annual proportion of signed small trades that are buyer initiated and returns in the subsequent year is strongest for such firms. This relationship supports the theory that the trades of individual investors move prices away from fundamental value.

[18] Table 2, Panel A, reports a monthly market-adjusted return for the value-weighted portfolios of stocks heavily sold (quintile 1) and bought (quintile 5) of 39 bps and 4 bps, respectively. The corresponding value-weighted returns with small, medium, and large firms are: small sold (-59 bps), small buy (52 bps), medium sold (40 bps), medium buy (-8 bps), big sold (49 bps), big buy (5 bps).

6 Conclusion

In theoretical models of investor sentiment, trading by not fully rational traders can drive prices away from fundamental values. Risk-averse informed traders cannot eliminate mispricing due to limits of arbitrage. When uninformed 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 signed small trades provide a reasonable proxy for the trading of individual investors. We externally validate that small trades from transactional data that have been signed using algorithms developed by Lee and Ready (1991) provide a reasonable proxy for the trading of individual investors; we do so 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.

Over short horizons our evidence is consistent with noise trader models in which the buying (selling) of retail 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.

Over annual horizons, our evidence that retail investors move prices is mixed. Smaller capitalization stock prices rise (fall) during years in which retail investors are net buyers (sellers), but medium and large capitalization stock prices fall (rise) during years in which retail investors are net buyers (sellers). While medium and large stock prices do rise (fall) during days of intense retail investor buying (selling), the negative correlation between annual retail investor buying and medium and large stock returns is consistent with the alternative explanation discussed in Section 5.

For small, medium, and large stocks, annual retail buy imbalances, forecast the next year's return. 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. The ability of small trades to forecast future returns is weakest for large capitalization firms and greatest for stocks for which arbitrage is difficult, such as those with greater idiosyncratic risk, and for stocks in which individual investors trade most intensely. For high idiosyncratic risk 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 a (four-factor) risk-adjusted 13.2 percentage points over the next year. For those stocks with the highest intensity of individual investor trades, this underperformance is an annual risk-adjusted 13.5 percentage points.

We conclude that over short and long horizons retail trade imbalances forecast future returns and that for all stocks over short horizons and for small stocks over annual horizons, retail trades also move markets.

References

Andrade, Sandro, Charles Chang, and Mark Seasholes, 2006, Trading imbalances, predictable reversals, and cross-sectional effects, working paper, University of California, Berkeley.

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

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003, Arbitrage Risk and Book-to-Market Anomaly, Journal of Financial Economics 69, 355-373.

Barber, Brad M., Lee, Yi-Tsung, Liu, Yu-Jane and Odean, Terrance, 2007, Just How Much Do Individual Investors Lose by Trading? forthcoming, *Review of Financial Studies*.

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, 2006, Up Close and Personal: An Individual Level Analysis of the Disposition Effect*, Management Science, 52-5, 726-74*.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2006, "Correlated Trading and Returns," working paper, Columbia University.

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.

Grinblatt, Mark and Sheridan Titman, 1989, Mutual fund performance: An analysis of quarterly portfolio holdings, *Journal of Business*, 3, 393-416.

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, 2006, Individual Investor Sentiment and Stock Returns http://ssrn.com/abstract=600084.

Kumar, Alok and Lee, Charles M. C., 2006, Retail Investor Sentiment and Return Comovements, Journal of Finance, 61-5, 2451-2486.

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.

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.

Mashruwala, Christina A., Shivaram Jajgopal, and Terry J. Shevlin, 2006, Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs, *Journal of Accounting & Economics, 42, 3-33.*

Mendenhall, Richard, 2004, Arbitrage risk and post-earnings-announcement drift, *Journal of Businesss*, 77, 875-894.

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, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting & Economics*, 42, 35-52.

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.

Wolff, Edward N., 2004, Changes in household wealth in the 1980s and 1990s in the U.S., working paper no. 407, The Levy Economics Institute of Bard College.

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 the 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) and correlations between the proportions buys for TAQ/ISSM trades size bins (Panel C). 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
	Panel C: Correlations between Trade Size Bins				
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 2: 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