Small Trades and the Cross-Section of Stock Returns

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This paper uses volume arising from small trades to analyze the relationship between retail investor trading behavior and the cross-section of future stock returns. The central finding is that stocks with intense sell-initiated small-trade volume, measured over the past several months, outperform stocks with intense buy-initiated small-trade volume. This return difference accrues from the first month after the portfolio formation up to two years later. Among small- and medium-sized firms, the return difference continues in the third year. The results suggest that stocks favored by retail investors subsequently experience prolonged underperformance relative to stocks out of favor with retail investors. (*JEL* G11, G12, G14)

A literature has emerged that finds systematic trading behavior among various investor groups. For instance, individual investors are found to quickly realize gains, but refrain from realizing losses; mutual funds and other institutional investors tend to follow momentum strategies, while individuals tend to be short-term contrarians, but longer-term momentum traders; a strong seasonal component exists to individuals' trading behavior; trading frequency by individuals depends on gender; small and large investors respond differently to events such as earnings releases, seasoned equity offerings, and analysts' recommendations.[1] Such systematic behavior is central to the line of reasoning espoused by the behavioral finance literature, which argues that sub-rational investors affect prices in financial markets. Otherwise, as Bagehot (1971) notes, even if investors are sub-rational, their trades will tend to cancel out, and any price effects will be minimal.

Even if behavior is systematic, the fundamental question remains as to what extent such behavior impacts prices in financial markets. This paper uses

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[1] See, for instance, Lee (1992), Grinblatt, Titman, and Wermers (1995), Odean (1998, 1999), Nofsinger and Sias (1999), Wermers (1999), Grinblatt and Keloharju (2000, 2001), Barber and Odean (2001, 2005), Goetzmann and Massa (2002), Hvidkjaer (2006), Huh and Subrahmanyam (2004), Kaniel, Saar, and Titman (2008), and Malmendier and Shanthikumar (2005).

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volume arising from small trades to investigate the relationship between retail investor trading behavior and stock returns. The central finding is that stocks with strong small-trade selling pressure, measured over the past several months, outperform stocks with strong small-trade buying pressure. This return difference persists at least two years after the portfolio formation. In other words, stocks favored by retail investors tend to experience prolonged underperformance in the future.

The measure of retail investor trading behavior is constructed from transactions of low dollar value in U.S. stocks in the 1983–2005 period. For each stock, sell-initiated volume is subtracted from buy-initiated volume, and the difference is divided by the number of shares outstanding. The result is the *signed small-trade turnover* (SSTT), and it is measured over periods of one to 24 months. Stocks with high SSTT (i.e., strong buying pressures) tend to have low book-to-market (BM) ratios, high past long-term returns, high turnover, and high advertising expenses. Also, SSTT is negatively correlated with contemporaneous changes in institutional holdings, although this relationship disappears in the last few of years in the sample. A large concurrent increase in small-trade turnover suggests that this disappearance is driven by increased splitting of institutional orders which, in turn, is partly driven by the shift to decimal pricing. Because the focus of this study is the trading behavior of retail investors, I exclude the period after the decimalization in 2001 from the main analysis.

Portfolios are formed on the basis of SSTT, and value-weighted returns of those portfolios are measured up to three years in the future. The results show that low SSTT stocks outperform high SSTT stocks. For instance, using a six-month formation period, the average monthly return difference between the two portfolios is 0.89% in the first year (t-statistic = 4.03) and 0.56% in the second year (t-statistic = 2.85). The third-year value-weighted return difference is an insignificant 0.17%, but further analysis shows significant return differences among small and medium-sized firms. In addition, returns are characteristic-adjusted based on size, BM, and momentum. This adjustment tends to lower the monthly return differences by 10–30 basis points, but has less impact on the statistical significance. For instance, the first-year return difference decreases to 0.67% per month, but the t-statistic falls only to 3.92.

The return differences appear in a number of subsamples based on different characteristics. Using the 13f data, I measure the fraction of trading volume that can be attributed to institutions, and find that return differences are especially large among stocks in which little trading volume can be attributed to institutions, that is, among stocks in which most of the volume is likely to reflect individuals' trades. Return differences are also particularly large among high-turnover stocks, low BM stocks, and NASDAQ stocks. The return differences tend to persist longer (hence the cumulative effect is larger) among small- and medium-sized stocks and among high momentum stocks. In the final years of the sample, in which the SSTT measure appears to be heavily influenced by institutional trading, the return differences diminish, although the short sub-sample period makes statistical inferences difficult.

Significant return seasonality exists in the short-term portfolios with a one-month formation and a one-month holding period. Consistent with the effect of tax-loss selling, returns of the selling pressure portfolio are low in December and high in January. The seasonality is accentuated among stocks in which little trading volume can be attributed to institutions, which is consistent with the effect being driven by individuals' tax considerations.

Little evidence exists to suggest that the return differences are caused by differences in risk. In addition to the characteristic-adjustment of returns, cross-sectional and time-series regression controls do not substantially decrease the return differential between the low and high SSTT stocks. Also, across SSTT portfolios, the high SSTT portfolio has the highest beta coefficient, yielding a negative beta of -0.42 for the zero-investment portfolio, which is long the low SSTT stocks and short the high SSTT stocks. This is inconsistent with the prediction of the Capital Asset Pricing Model that the relationship between beta and expected returns is positive.

The findings are consistent with the hypothesis that stocks favored by retail investors are overvalued and subsequently experience prolonged underperformance relative to stocks out of favor with retail investors. Alternatively, the findings might possibly be understood in rational frameworks by appealing either to the limits to liquidity or to informational asymmetry. For example, Campbell, Grossman, and Wang (1993) suggest that selling pressures lead to temporarily higher expected returns in order to induce liquidity providers to enter the market. However, such liquidity effects would presumably be relatively short-run, such as days or perhaps weeks. Yet, this paper finds significant return differences both in the second and third year after the portfolio formation, suggesting that the results do not merely reflect a liquidity premium. In asymmetric information models, privately informed investors necessarily capture higher returns than do uninformed investors when prices are not fully revealing. If informed investors enjoy higher returns over some time interval, the information would generally have to be private at the beginning of that interval. Therefore, if the results are to be understood within a purely rational asymmetric information framework, then they show that private information is truly long-lived. Still, because SSTT is constructed from publicly available information, such an interpretation is subject to the caveat that prices do not appear to fully reflect public information.

In related research, Hvidkjaer (2006) also constructs a measure of small-trade imbalance, defined as the percentage difference between buy- and sell-initiated small-trade volume in a given stock. In comparison, the current paper scales signed volume by shares outstanding instead of by volume. While both approaches would seem to be reasonable measures of retail investor trading behavior, the scaling in the current paper follows the approach in Breen, Hodrick, and Korajczyk (2002). These authors argue that the relationship between signed turnover and returns is an accurate measure of price impact. Therefore, one might expect any price effect to be stronger when scaling by shares outstanding instead of volume.

Hvidkjaer (2006) analyzes the trading behavior of small (and large) investors in Jegadeesh and Titman (1993) momentum portfolios, and whether this contributes to the profitability of momentum strategies. Indeed, Hvidkjaer (2006) finds that momentum stocks with small-trade selling pressures outperform those with small-trade buying pressures. Given that result, it is not surprising that SSTT has explanatory power for future returns. Rather, the surprise lies in the magnitude, persistence, and wide scope of the explanatory power.

In a paper developed contemporaneously and independently of the current paper, Barber, Odean, and Zhu (2006) also use transactions data to study the relationship between signed volume and future returns. As Hvidkjaer (2006), they scale the difference between buy- and sell-initiated small-trade (large-trade) volume by the total small-trade (large-trade) volume. Using a one-year formation period and a one-year holding period they find, as does the current study, that stocks with strong retail investor buying over the prior year underperform those with strong retail investor selling. Also, they detect that stocks purchased by retail investors at the weekly level actually perform well over the following week.[2] The short-term results in Barber, Odean, and Zhu (2006) are consistent with the findings of Kaniel, Saar, and Titman (2008), who have access to data on orders routed to the New York Stock Exchange (NYSE) during a four-year period. Kaniel, Saar, and Titman (2008) note that the short-term profitability of retail trades is consistent with risk-averse individuals being compensated for providing liquidity to institutional investors. Also consistent with compensation to liquidity providers, Subrahmanyam (2006) finds that signed dollar volume is negatively related to returns over the next one to two months. At the daily and intradaily horizons, Chordia and Subrahmanyam (2004) and Chordia, Roll, and Subrahmanyam (2005) also find that signed volume predicts future returns.

Several other studies link trading by individuals to future returns. Using brokerage account data, Coval, Hirshleifer, and Shumway (2005) find persistence in the trading performance of individual investors, and that some individuals are consistently able to outperform the market. In other markets, Grinblatt and Keloharju (2000) and Barber et al. (2005) find that the trades of individual investors in Finland and Taiwan, respectively, yield significantly lower returns than those of institutional investors.

A paper also similar in spirit is Frazzini and Lamont (2005), who study the effect of mutual fund flows on stock return. Like the current study, they find that stocks favored by retail investors tend to underperform in subsequent years. Their argument is that mutual funds are constrained in their holdings, so that currently popular funds with strong inflows of money might have to invest in stocks that they already consider overvalued. This provides an alternative and indirect channel through which retail investors could affect stock prices.

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[2] Barber et al. (2006) compare the findings in the two papers and find a similar result for SSTT at the weekly level.

The remainder of the paper is organized as follows. Section 1 details the sample and the construction of the SSTT variable. Section 2 presents various characteristics of the SSTT-sorted portfolios and the time variation in some of the key characteristics. Section 3 contains the main results of the paper, namely the explanatory power of SSTT for the cross-section of future returns. Section 4 concludes the paper.

1. Data Sample and Construction of Variables

The sample in the current study includes all ordinary common stocks listed on the NYSE and the American Stock Exchange (AMEX) in the period January 1983 through December 2005. Transactions data on NASDAQ stocks became available in January 1987, hence those stocks are included in the sample from that time on. Real estate investment trusts, stocks of companies incorporated outside the U.S., and closed-end funds are eliminated from the sample. Return data and unsigned share volume data are from the Center for Research in Security Prices (CRSP) files. Data on book value of equity are from Compustat, and book value is defined as in Fama and French (1992). Institutional ownership data are from the 13f transactions files compiled by CDA/Spectrum. Returns from factor-mimicking portfolios, which are used in time-series regressions, are available from two sources. First, the Fama-French and momentum factor returns were obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/, which also details the procedure used to create the portfolio returns. Secondly, the probability of informed trading (PIN) factor returns constructed in Easley, Hvidkjaer, and O'Hara (2005) are available at http://www.hvidkjaer.net.

Transactions data are obtained from the Institute for the Study of Security Markets (ISSM) and the Trade And Quote (TAQ) data sets. The ISSM data set includes all transactions and quotes in all stocks listed on NYSE/AMEX in 1983–1992 and NASDAQ in 1987–1992, while TAQ covers 1993 to present. Trades and quotes with irregular terms are excluded, and trades and quotes are run through a simple price-based error filter to exclude likely erroneous prices.[3]

The ISSM and TAQ data sets do not contain any information on whether a trade was initiated by the buyer or the seller. The classification of trades as buys or sells is therefore done according to the Lee and Ready (1991) algorithm. This is standard in the market microstructure literature, and primarily uses trade placement relative to the current bid/ask quotes to determine trade direction. If a trade is executed at a price above (below) the quote midpoint, it is classified as a buy (sell). Trades at the quote midpoint are classified using the "tick test," which determines the direction by comparing the trade price to the price of preceding trades. All eligible trades are thus classified as either buys or sells.

Furthermore, all trades are classified by size using a variation of the Lee (1992) dollar-based trade-size proxy. Lee notes that while a dollar-based size

[3] See the appendix in Hvidkjaer (2006) for a description of the trade and quote filters.

proxy is conceptually superior to one based on the number of shares traded, the dollar-based proxy is sensitive to small price changes. Therefore, he suggests obtaining a closing price during the sample period, comparing that price to, say, \$10,000, and determine the largest number of round lots that is less than or equal to \$10,000. Trades at this number of shares or less are deemed small trades. Moreover, using the TORQ data set, which has order-level data, Lee and Radhakrishna (2000) provide support for the use of trade size as a proxy for individual versus institutional trading. They also find that the classification accuracy can be enhanced by conditioning the cut-off point on firm size.

Hvidkjaer (2006) suggests sorting stocks into quintiles based on NYSE/AMEX firm-size cut-off points and using the following small-trade cut-off points within firm-size quintiles: \$3,400 for the smallest firms, and \$4,800, \$7,300, \$10,300, and \$16,400 for the largest firms. The cut-off points in number of shares are updated monthly based on the share price at the end of the prior month. I slightly modify the approach in Hvidkjaer (2006), as the share cut-off points are obtained as the ratio of the dollar cut-off point to the share price *rounded up* to the nearest round-lot. This ensures that small trades exist in all stocks.

The small-trade buy-volume is summed up monthly, and the small-trade buy-initiated turnover is computed as the total number of shares of small buy-initiated trades in that month, divided by the number of shares outstanding. The small-trade sell-initiated turnover is computed similarly. At the end of each month, the small-trade buy- and sell-initiated turnover are then summed over the prior J months, where $J = 1, 3, 6, 12,$ and 24. The SSTT is then simply the summed small-trade buy-initiated turnover minus the summed small-trade sell-initiated turnover.[4] SSTT is the main conditioning variable used in the asset pricing tests in Section 3, where portfolios are formed monthly based on the J-month SSTT. In the portfolio formation, only stocks with a current price of at least \$5 are included. This tends to ensure investability and that the return results are not influenced by bid-ask bounces.[5]

2. The Characteristics of SSTT-Sorted Portfolios

Before analyzing the returns to SSTT-sorted portfolios, it is useful to examine the characteristics of stocks that have low or high SSTT. In Table 1, stocks are sorted into deciles each month according to past six-month SSTT. Value-weighted characteristics of the stocks in the sample are computed monthly, and the time-series averages in each of the portfolios are reported along with the difference between the low and high SSTT portfolio and the corresponding

[4] The reported trading volume of NASDAQ-listed stocks is inflated relative to that of stocks on the NYSE/AMEX (Gould and Kleidon, 1994). However, the Appendix shows that there is little systematic difference in small-trade turnover across exchanges. Therefore, no attempts were made to deflate NASDAQ trading volume.

[5] Tests were initially run including all stocks with a price of at least \$1. However, it turned out that small-trade turnover constitutes a very large fraction of overall turnover for the lowest priced stocks. Consequently, those stocks tended to be overrepresented in the extreme SSTT portfolios.

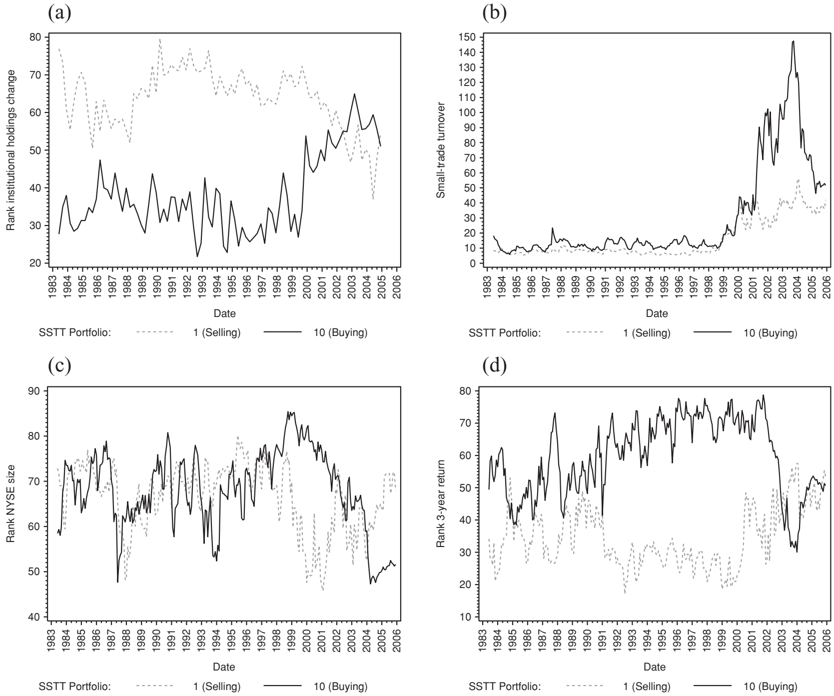

Figure 1
Characteristics of SSTT portfolios
Deciles are formed monthly in 1983–2005 based on past six-month SSTT, and the figures contain time-series of average characteristics for the stocks in the low and high SSTT portfolios. In Figure 1(a), the change in institutional holdings over the six-month period is computed as the change in the number of shares held by institutions divided by the number of shares outstanding. Then, within NYSE size quintiles, stocks are ranked each month based on the institutional holdings change, and the monthly value-weighted mean ranks are shown. In Figure 1(b), the annualized percentage small-trade turnover over the six-month period is computed for each stock, and the monthly value-weighted means of the small-trade turnover are shown. In Figure 1(c), stocks are ranked by NYSE size cut-off points, and the monthly value-weighted mean ranks are shown. In Figure 1(d), stocks are ranked each month based on $ret_{-41:-6}$, the three-year return prior the six-month period, and the monthly value-weighted mean of the ranks are shown. All ranks are in percentages.

autocorrelation-adjusted t-statistics. The table also presents the Wald statistics from testing for equality of the characteristics across all portfolios. The portfolios might not have stable characteristics, since different styles could vary in popularity through time. Hence, Figure 1 shows the time series patterns of some key characteristics.

It is possible that small trades originate from large orders that have been broken up. The question then is whether or not SSTT in fact captures retail investor behavior. One way to test this is to compare SSTT with the contemporaneous change in institutional holdings, as reported each quarter in the 13f data. If indeed high SSTT indicates that retail investors are net-buyers of a stock, we might expect institutional investors to be net-sellers. The relationship, though, is complicated by a number of effects, which could make the 13f data a less

Table 1
Characteristics of SSTT portfolios

	Low	2	3	4	5	6	7	8	9	High	Low–High	t(Low–High)	Wald χ^2_9
Δ Inst. hold. (%)	3.49	1.94	1.42	0.95	0.75	0.71	0.69	0.64	0.31	−0.31	3.80	6.33	89.8
NYSE size rank (%)	67.65	75.62	80.74	84.36	85.89	86.80	86.38	83.54	79.70	70.16	−2.51	−1.62	749.8
$ret_{-5:0}$ (%)	23.21	16.91	13.83	12.73	11.97	10.52	11.21	11.38	13.41	18.14	5.07	1.50	42.2
$ret_{-41:-6}$ (%)	42.74	49.64	64.66	72.66	83.23	104.43	124.25	141.68	176.98	224.41	−181.67	−7.77	262.1
Rank turnover (%)	72.09	62.98	55.99	51.71	51.40	52.25	56.01	62.37	69.40	82.36	−10.27	−9.05	1741.8
Small-trade turnover (%)	4.88	2.50	1.72	1.29	1.05	1.03	1.26	1.85	2.91	7.06	−2.18	−10.10	391.7
SSTT (%)	−0.84	−0.33	−0.18	−0.09	−0.03	0.03	0.10	0.21	0.42	1.23	−2.08	−37.12	2955.9
Advertising/sales (%)	4.63	3.90	3.89	4.12	4.22	4.46	4.87	4.72	5.34	6.49	−1.85	−1.85	35.9
Price ($)	28.01	37.04	44.08	69.30	101.45	251.01	69.26	47.27	40.64	31.99	−3.98	−1.89	379.2
BM	0.82	0.74	0.68	0.63	0.57	0.49	0.44	0.45	0.43	0.47	0.35	20.28	159.9
Age (years)	22.62	26.40	25.81	26.82	28.32	28.25	27.87	26.38	24.01	18.66	3.96	5.98	248.3
No. of stocks	364.21	365.12	365.26	365.30	365.25	365.83	365.71	365.64	365.74	365.24			

Deciles are formed monthly from June 1983 to January 2001 based on prior six-month SSTT ($J = 6$), and the sample consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price ≥$5. All characteristics are value-weighted within each decile, and the table presents averages across formation dates. $ret_{-5:0}$ is the return during the six-month formation period. $ret_{-41:-6}$ is the prior three-year return. The six-month share turnover is ranked within the NYSE/AMEX and NASDAQ separately, and the average percentage rank of the stocks in each portfolio is reported. *Small-trade turnover* is the sum of the small-trade buy- and sell-initiated turnover. BM is the book-to-market ratio of equity. *Age* is the time since the first entry in the CRSP files. Changes in institutional holdings (Δ *inst. hold.*), as a percentage of shares outstanding, during the six-month formation period are computed every third month. The table reports the difference between the high and low SSTT portfolio for each characteristic, along with the t-statistics. Wald tests for equality of the characteristics across all portfolios are also given. Wald and t-statistics are computed controlling for heteroskedasticity and for autocorrelation induced by the overlapping formation periods.

accurate source of information about retail investor behavior and preferences. First, SSTT measures the direction of market orders, while changes in holdings reflect both market and limit orders. Because market orders are almost certain to be executed, a purchase based on a market order represents a clear preference towards a stock. By contrast, an individual might, say, submit buy limit orders in stocks A and B, but only receive trade execution in stock A. This does not represent a preference towards stock A relative to B, yet would be recorded as such using holdings data. Secondly, SSTT is meant to capture the trading of retail, or small, investors rather than individual investors in general. Trades by wealthy individuals are likely to be economically significant, but might reflect considerations that are different from those of small retail investors. Thirdly, short positions are not reported in the 13f data. If, say, a hedge fund short-sells shares to another institutional investor, a net increase in institutional holdings would be recorded, even though no individual investors participated in the transaction. Finally, any window dressing by mutual funds will skew the snap-shot picture that the 13f data provide. If a mutual fund engages in window dressing, it would take short-term positions in winner stocks around the date of reporting in order to create the impression of a successful portfolio. While it is difficult to know the extent of window dressing, it does illustrate the difficulty of making inferences based on such low-frequency data.[6]

Despite such caveats, the change in institutional holdings during the contemporaneous six-month period is negatively correlated with SSTT. Figure 1(a) depicts the time-series pattern of the institutional trading in the low and high SSTT stocks. The percentage rank change in institutional holdings as a fraction of shares outstanding is computed within NYSE size quintiles, and the figure presents the value-weighted mean rank of the stocks in the low and high SSTT portfolios. Ignoring the effect of value-weighting, a perfect negative correlation between SSTT and the change in institutional holdings would imply that the stocks in the low (high) SSTT decile have an average rank of 95% (5%). Figure 1(a) shows that low (high) SSTT stocks indeed tend to be bought (sold) by institutional investors during most of the sample period. For instance, the stocks in the low (high) SSTT portfolio on the first formation date in June 1983 have an average rank of 77% (28%). However, the negative correlation disappears in the final years of the sample period. This might be due to the increased automated trading, decreased trading costs, and increased order splitting by institutional traders following the decimalization in 2001.[7] If correct, then we would expect small-trade turnover to increase in those years, as more investors now trade smaller sizes. Figure 1(b) shows the annualized small-trade turnover in the two

[6] Because such factors limit the ability of the 13f data to provide accurate information about retail investor behavior and preferences, the 13f data would not necessarily contain information similar to SSTT about future returns.

[7] For instance, Chakravarty, Panchapagesan, and Wood (2005) find that while trading costs decrease overall following the decimalization on the NYSE, costs actually increase for orders executed in a quick manner. They also find that institutions are breaking up their orders in response to changes in liquidity following the decimalization. As they note [p. 419], "[i]n that sense, institutions appear to be morphing somewhat into individual investors."

extreme SSTT portfolios. The pattern is clear: while the small-trade turnover is fairly stable throughout most of the sample period at less than 20%, a huge increase appears in the later years. It is particularly large for the stocks in the high SSTT portfolio with the average small-trade turnover spiking at more than 140% in 2003. While some of the increase surely is driven by actual increase in trading by retail investors, in particular the early increases around 1999 during the high-return period on NASDAQ, the bulk is likely to come from institutional trading. Therefore, the main analysis below excludes the final years of the sample, and a natural cut-off point is when NYSE and AMEX stocks began trading in decimals, namely at the end of January 2001. That is, January 2001 is the last month in which portfolios are formed. Returns during the post-decimalization period are analyzed separately in Section 3.3.

Confirming the results in Figure 1(a), Table 1 shows that the portfolio with the strongest small-trade selling pressure has the highest change in institutional holdings with a 3.49% increase as a percentage of shares outstanding during the six-month period. The change in institutional holdings decreases monotonically across SSTT portfolios to −0.31% for the high SSTT portfolio.[8]

Table 1 also shows the mean percentage size ranks based on NYSE cut-off points. SSTT does not appear to be strongly correlated with firm size, although stocks in the extreme SSTT portfolios tend to be somewhat smaller than those in the intermediate portfolios. Still, the value-weighted mean ranks of 67.7% and 70.2% of the low and the high SSTT portfolios, respectively, are well above the median NYSE stock. Figure 1(c) plots the rank size each month for the SSTT portfolios. The figure reveals that the average difference in size between the two portfolios is driven by a preference for larger stocks in the 1998–2001 period. The figure also shows a drop in 1987, which is simply caused by the inclusion of NASDAQ stocks in the sample.

Both overall turnover and small-trade turnover are large in the extreme SSTT portfolios. Overall turnover in Table 1 is ranked within NYSE/AMEX and NASDAQ separately, and the table reports the value-weighted percentage ranks for each portfolio. The low SSTT portfolio has a high average turnover rank of 72.1%, but the high SSTT portfolio is even higher at 82.4%. The turnover statistics suggest that both the high and low SSTT portfolios consist of relatively liquid stocks.

Advertising expenses have been linked to breath of ownership and liquidity (Grullon, Kanatas, and Weston, 2004 and Frieder and Subrahmanyam, 2005), and mutual fund advertising has been found to affect investor portfolio choice (Cronqvist, 2006). We might expect advertising to especially affect retail investors' decisions, and Table 1 indeed shows that the high SSTT firms on average spend most on advertising as a percentage of sales. While the difference in advertising expenses between the high and low SSTT portfolios is only marginally significant (t-statistic = 1.85), the Wald test for differences

[8] See also Campbell, Ramadorai, and Schwartz (forthcoming) for a thorough analysis of the ability of the transactions data to predict the quarterly changes in institutional holdings in the 1993–2000 period.

across all ten portfolios is highly significant with a statistic of 35.9. Since the underlying distribution of the Wald test is χ^2_9, the p-value is .000.[9]

Table 1 suggests that the low-SSTT stocks tend to be high book-to-market, or value, stocks. By contrast, while the stocks in the highest SSTT portfolio do have a relatively low book-to-market ratio on average, the ratio is not lower than that of the four other upper half SSTT portfolios. The table also shows that SSTT is highly correlated with the prior three-year returns. Figure (d) shows the rank three-year return for the low and high SSTT portfolios over the sample period. While the high SSTT stocks clearly have higher past returns throughout most of the sample, the relationship does vary over time. For instance, the spread appears to be very wide just prior to the October 1987 crash, after which it disappears for a short period. The return spread disappears again in 2002, but this might be related to the increased institutional presence among small trades.

3. SSTT and the Cross-Section of Returns

The main question addressed in this paper is whether SSTT, the measure of retail investor trading behavior, has explanatory power for the cross-section of future stocks returns. This section shows that portfolios of stocks with low SSTT outperform portfolios of stocks with high SSTT, using a number of methods and within a number of subsamples.

Each month stocks are sorted into value-weighted portfolios according to SSTT measured over the prior J months, where J is equal to 1, 3, 6, 12, and 24. Future returns earned by these portfolios are computed over horizons of K months, where K is equal to 1, 2–7, 1–12, 13–24, and 25–36 months. Both raw and characteristic-adjusted returns are reported. Returns are characteristic-adjusted based on size, BM and momentum in a manner similar to the technique suggested by Daniel et al. (1997) and Wermers (2004). Specifically, each month, stocks are sorted into size quintiles based on NYSE cut-off points, and within each size quintile, stocks are sorted into quintiles based on industry-adjusted BM ratios.[10] Within each of the size-BM portfolios, stocks are sorted into quintiles according to their past 12 months return. Each stock is now uniquely identified with one of the resulting 125 portfolios, and the size-, BM-, and momentum-adjusted return for stock i in month t is then its return minus the value-weighted mean return of the other stocks in the portfolio. If expected returns only depend on these characteristics, then the expected characteristic-adjusted return of a given stock would be zero.

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[9] Advertising expenses are higher for the firms in the low SSTT decile than for those in deciles 2–6. This might be related to the fact that (unsigned) small-trade turnover also is higher for the low SSTT stocks. Indeed, a sort into deciles by small-trade turnover shows that high small-trade turnover stocks have significantly higher advertising expenses than low small-trade turnover stocks.

[10] The industry-adjustment is based on the Fama-French 17-industry classification and is performed as in Wermers (2004), who normalizes log(BM) within industry by subtracting the industry mean and dividing by the standard deviation.

Table 2
Returns to SSTT portfolios

		Monthly % returns, holding period K =				
Formation period	Portfolio	1	2–7	1–12	13–24	25–36
$J = 1$	1	1.54	1.42	1.48	1.28	1.57
	2	1.47	1.45	1.50	1.20	1.40
	3–8	1.31	1.24	1.22	1.07	1.25
	9	1.35	1.09	1.11	0.96	1.36
	10	0.79	0.67	0.77	0.84	1.37
	1–10	0.75	0.75	0.71	0.44	0.20
		(2.45)	(3.72)	(4.34)	(2.84)	(1.14)
$J = 3$	1	1.53	1.50	1.58	1.35	1.58
	2	1.59	1.47	1.52	1.23	1.45
	3–8	1.28	1.20	1.21	1.10	1.26
	9	1.20	1.01	0.98	0.96	1.35
	10	0.68	0.64	0.76	0.83	1.37
	1–10	0.85	0.86	0.82	0.53	0.20
		(2.92)	(3.89)	(4.37)	(2.93)	(0.98)
$J = 6$	1	1.65	1.59	1.61	1.37	1.54
	2	1.45	1.56	1.48	1.23	1.38
	3–8	1.25	1.21	1.17	1.13	1.25
	9	1.16	1.01	0.99	1.00	1.28
	10	0.70	0.71	0.72	0.80	1.37
	1–10	0.94	0.87	0.89	0.56	0.17
		(3.46)	(3.59)	(4.03)	(2.85)	(0.68)
$J = 12$	1	1.74	1.68	1.66	1.27	1.50
	2	1.64	1.64	1.55	1.27	1.31
	3–8	1.28	1.23	1.21	1.13	1.24
	9	1.20	1.13	1.11	1.00	1.31
	10	0.80	0.78	0.77	0.76	1.33
	1–10	0.93	0.90	0.89	0.50	0.17
		(3.02)	(3.29)	(3.52)	(1.98)	(0.56)
$J = 24$	1	1.62	1.47	1.50	1.24	1.46
	2	1.74	1.60	1.51	1.07	1.23
	3–8	1.34	1.26	1.29	1.08	1.21
	9	1.36	1.18	1.20	1.03	1.43
	10	0.95	0.74	0.77	0.76	1.23
	1–10	0.67	0.73	0.73	0.48	0.22
		(2.21)	(2.46)	(2.61)	(1.48)	(0.63)

Deciles are formed monthly from January 1983 to January 2001 based on prior J-month SSTT, and the sample consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price ≥ \$5. Stocks with low (high) SSTT are in decile 1 (10), and returns are value-weighted within deciles. The table presents the average monthly returns computed over holding periods K. For instance, $K = 1$–12 represents average returns in months 1–12 after the portfolio formation, computed by averaging the current month's return of the strategies initiated over the prior 12 months. The difference in returns between the low and the high SSTT portfolios are also reported, along with t-statistics in parentheses.

Similar to Jegadeesh and Titman (1993), holding-period portfolio returns are calculated as the average of the current period's return on the previous K months' portfolios. For K equal to 1–12, for example, the portfolio return is the average of this month's return for the portfolios constructed in each of the prior twelve months. By averaging across prior strategies rather than prior returns, the overlap problem is avoided and t-statistics can be computed in the normal manner. All t-statistics are computed using the White correction for heteroskedasticity.

Table 2 shows the average monthly returns for the stocks in SSTT deciles 1, 2, 9, and 10, and for a portfolio consisting of the stocks in the intermediate six deciles. The results show that low SSTT stocks (decile 1) tend to outperform high SSTT stocks (decile 10) up to two years after the formation date. For instance, using a six-month formation period, low SSTT stocks outperform high SSTT stocks by 0.94% in the first month after the portfolio formation (t-statistic = 3.46) and by 0.87% per month over the following six months (t-statistic = 3.59). In year two, the monthly return difference is still a highly significant 0.56% (t-statistic = 2.85), while it becomes insignificant in year three.

To the extent that characteristic-adjusting returns capture differences in risk or that SSTT measures small-trader preferences towards particular styles as opposed to individual stocks, we would expect the characteristic-adjusted return differences to be smaller than those of the raw returns. Indeed, the differences of the characteristic-adjusted returns presented in Table 3 are somewhat lower than those of the raw returns. For instance, for $J = 6$, $K = 2$–7, the difference of the value-weighted returns is now 0.69%, a reduction of 0.18 percentage points from the raw returns. However, the corresponding t-statistic is almost unchanged—from 3.59 to 3.58. Generally, the t-statistics in Table 3 are similar to those of the raw return differences, so the statistical significance of the results is unaffected by the characteristic-adjustment.

The adjusted returns also allow one to analyze the extent to which high versus low SSTT stocks contribute to the return differences. The two sides seem to contribute about equally: for the $J = 6$, $K = 2$–7 strategy, low SSTT stocks outperform their benchmark by 0.34% (t-statistic = 2.20), while high SSTT stocks underperform their benchmark by 0.35% (t-statistic = −1.88).

The results in Tables 2 and 3 are remarkably robust to different choices of J, the length of the formation period. Also, as a robustness check, one can examine the difference in returns between deciles 2 and 9. Indeed, for the strategies in Table 2 that yield significantly positive return differences between deciles 1 and 10, the corresponding difference between deciles 2 and 9 is also positive in every case. Moreover, in Table 3, for the strategies with significant decile spreads, all decile 2 adjusted returns are positive and all decile 9 adjusted returns are negative. In sum, the relationship between SSTT and future returns also seems to appear outside the two extreme SSTT deciles.

3.1 Interaction effects with other stock characteristics

The results so far show that small trades contain information about the cross-section of future returns. In order to understand the nature of this relationship and further examine its robustness, this section analyzes how it varies across portfolios sorted by different characteristics of the stocks.

If the relationship indeed is driven by retail investor trading behavior, a natural hypothesis is that the strength of the return predictability is positively correlated with the degree to which the trading population consists of retail investors. That is, we would expect a higher return differential between the

Table 3
Characteristic-adjusted returns to SSTT portfolios

		Monthly % adj. returns, holding period K =				
Formation period	Portfolio	1	2–7	1–12	13–24	25–36
$J = 1$	1	0.18	0.22	0.29	0.24	0.17
		(0.97)	(1.33)	(1.86)	(1.30)	(1.16)
	2	0.12	0.17	0.20	0.08	0.03
		(0.90)	(1.59)	(2.19)	(0.84)	(0.40)
	9	−0.03	−0.12	−0.07	−0.04	0.07
		(−0.27)	(−1.48)	(−0.93)	(−0.45)	(0.80)
	10	−0.47	−0.37	−0.31	−0.12	0.08
		(−2.42)	(−2.17)	(−1.79)	(−0.72)	(0.42)
	1–10	0.65	0.59	0.60	0.36	0.09
		(2.72)	(3.50)	(4.37)	(2.59)	(0.64)
$J = 3$	1	0.19	0.31	0.36	0.27	0.19
		(1.04)	(1.88)	(2.33)	(1.57)	(1.36)
	2	0.18	0.21	0.22	0.10	0.07
		(1.38)	(1.67)	(2.02)	(1.02)	(0.86)
	9	−0.08	−0.16	−0.17	−0.09	0.05
		(−0.74)	(−2.01)	(−2.12)	(−0.95)	(0.49)
	10	−0.47	−0.36	−0.28	−0.11	0.09
		(−2.24)	(−2.01)	(−1.63)	(−0.66)	(0.48)
	1–10	0.66	0.67	0.64	0.38	0.10
		(2.84)	(3.75)	(4.19)	(2.42)	(0.62)
$J = 6$	1	0.25	0.34	0.38	0.25	0.20
		(1.56)	(2.20)	(2.57)	(1.68)	(1.54)
	2	0.07	0.24	0.20	0.04	0.03
		(0.50)	(2.36)	(1.82)	(0.40)	(0.36)
	9	−0.04	−0.14	−0.11	−0.07	−0.01
		(−0.37)	(−1.79)	(−1.48)	(−0.76)	(−0.16)
	10	−0.37	−0.35	−0.29	−0.17	0.09
		(−1.86)	(−1.88)	(−1.56)	(−0.97)	(0.46)
	1–10	0.63	0.69	0.67	0.42	0.11
		(2.85)	(3.58)	(3.92)	(2.66)	(0.56)
$J = 12$	1	0.29	0.33	0.35	0.19	0.18
		(1.82)	(2.60)	(2.58)	(1.44)	(1.48)
	2	0.26	0.26	0.27	0.10	−0.05
		(2.18)	(2.55)	(2.61)	(1.04)	(−0.55)
	9	−0.11	−0.08	−0.05	−0.06	0.06
		(−0.95)	(−0.94)	(−0.54)	(−0.58)	(0.54)
	10	−0.42	−0.29	−0.25	−0.18	0.07
		(−2.03)	(−1.52)	(−1.32)	(−0.87)	(0.32)
	1–10	0.71	0.62	0.60	0.37	0.11
		(2.67)	(2.95)	(3.10)	(1.91)	(0.48)
$J = 24$	1	0.16	0.14	0.21	0.18	0.16
		(1.16)	(1.08)	(1.38)	(1.37)	(1.16)
	2	0.45	0.27	0.19	−0.04	−0.12
		(4.02)	(2.58)	(1.95)	(−0.40)	(−1.07)
	9	−0.03	−0.05	−0.03	0.02	0.15
		(−0.31)	(−0.45)	(−0.26)	(0.15)	(1.18)
	10	−0.36	−0.37	−0.31	−0.10	−0.06
		(−1.89)	(−1.87)	(−1.61)	(−0.42)	(−0.24)
	1–10	0.51	0.51	0.52	0.28	0.22
		(2.19)	(2.30)	(2.48)	(1.11)	(0.80)

Deciles are formed monthly from January 1983 to January 2001 based on prior J-month SSTT, and the sample consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price ≥\$5. Stocks with low (high) SSTT are in decile 1 (10), and returns are value-weighted within deciles. The table presents the average monthly characteristic-adjusted returns computed over holding periods K. For instance, K = 1–12 represents average returns in months 1–12 after the portfolio formation, computed by averaging the current month's return of the strategies initiated over the prior 12 months. Returns are adjusted by subtracting the returns of a matched portfolio based on size, industry-adjusted BM ratios, and momentum quintiles from the monthly returns of each individual stock. The difference in returns between the low and the high wwwnSSTT portfolios are also reported. t-statistics are in parentheses.

low and high SSTT portfolios among stocks where the traders predominantly are retail investors. Panels A and B of Table 4 examine the ability of SSTT to predict future returns within portfolios based on two characteristics expected to be (negatively) correlated with the fraction of traders who are retail investors, namely firm size and the level of institutional trading. Stocks are sorted according to the characteristic into three groups, and within each group, SSTT deciles are formed as before. The table reports the average of the monthly value-weighted raw and characteristic-adjusted returns for the stocks in SSTT deciles 1 and 10. The formation period is six months ($J = 6$), and the holding periods are $K = 1$–12, 13–24, and 25–36 months. Also, the table reports, for each portfolio, the average number of stocks, the value-weighted mean percentage NYSE size rank, and the value-weighted mean SSTT.

In Panel A of Table 4, stocks are sorted into three groups according to NYSE size rank with cut-off points at 30% and 70%. The average SSTT for each portfolio in Panel A is consistent with the notion that retail investors are more predominant among smaller firms. In the buying pressure portfolio, for instance, SSTT is 1.67% of shares outstanding among the smallest firms, while it is only 0.79% among the largest firms. Consequently, the SSTT spread between portfolios 1 and 10 is larger among smaller firms. The table shows that SSTT has explanatory power for returns across all size groups. Among stocks in the small- and medium-sized groups, the effect is large and persistent with significant return differences even in year 3. That is, in the third year after the portfolio formation date, the average difference in the characteristic-adjusted returns of low and high SSTT stocks is 0.44% per month (t-statistic = 2.74) among small firms and 0.35% (t-statistic = 2.17) among medium-sized firms. Among stocks larger than the NYSE 70th size percentile, the return differences are relatively large in the first year after the formation date, but insignificant in years 2 and 3. For instance, the difference in adjusted returns is 0.47% per month (t-statistic = 2.10) in year 1. As shown in the last line of the table, this is 0.20 percentage point lower than the corresponding strategy among small firms, but the return difference between the two zero-investment portfolios is insignificant. This return difference only becomes significant in year 3. In sum, only weak evidence suggests that the initial return differences are larger among smaller firms, but the return differences are clearly more persistent among smaller firms. In other words, the cumulative return differences across SSTT portfolios are larger for smaller firms, consistent with larger mispricing among such firms.

A more direct and potentially more powerful way to identify stocks with a high level of retail investor participation is based on the fraction of trading volume that can be linked to changes in institutional holdings. If less of the reported trading volume in a stock can be traced to institutions, then, all else equal, a larger fraction of volume would reflect retail investor trading.

From the 13f data, quarterly institutional trading volume is computed for each stock i as the sum across the J institutions of the absolute value of the

Table 4
Interaction with stock characteristics

Panel A: Sorts by NYSE rank size, then SSTT

					% Raw returns, $K =$			% Adj. returns, $K =$		
Size group	SSTT portfolio	nStk	NYSE szRnk	SSTT	1–12	13–24	25–36	1–12	13–24	25–36
1	1	213	16	−1.00	1.16	1.15	1.69	0.13	0.12	0.35
(Small)	10	214	18	1.67	0.29	0.53	1.19	−0.54	−0.32	−0.09
	1–10			−2.67	0.87	0.62	0.50	0.66	0.44	0.44
					(5.03)	(3.83)	(2.68)	(5.11)	(3.04)	(2.74)
2	1	99	53	−0.80	1.34	1.23	1.61	0.13	0.12	0.25
	10	100	52	1.31	0.70	0.76	1.20	−0.31	−0.29	−0.10
	1–10			−2.11	0.64	0.48	0.41	0.43	0.41	0.35
					(2.83)	(2.80)	(2.04)	(2.72)	(2.90)	(2.17)
3	1	51	88	−0.54	1.58	1.37	1.39	0.35	0.21	0.11
(Large)	10	51	89	0.79	0.97	1.02	1.60	−0.12	−0.04	0.24
	1–10			−1.33	0.61	0.34	−0.22	0.47	0.24	−0.13
					(1.96)	(1.15)	(−0.68)	(2.10)	(1.16)	(−0.56)
1−3	1–10			−1.34	0.26	0.28	0.72	0.20	0.20	0.57
					(0.88)	(0.96)	(2.35)	(0.79)	(0.80)	(2.11)

Panel B: Sorts by exchange ranked FVI6 (institutional trading), then SSTT

					% Raw returns, $K =$			% Adj. returns, $K =$		
FVI6 group	SSTT portfolio	nStk	NYSE szRnk	SSTT	1–12	13–24	25–36	1–12	13–24	25–36
1	1	109	62	−1.12	1.30	1.54	1.83	0.11	0.45	0.45
(Low)	10	109	60	1.98	0.01	0.33	1.16	−1.02	−0.64	−0.00
	1–10			−3.10	1.28	1.21	0.67	1.13	1.09	0.46
					(4.06)	(3.79)	(1.96)	(4.08)	(3.65)	(1.46)
2	1	145	69	−0.88	1.66	1.28	1.47	0.39	0.22	0.12
	10	146	70	1.22	0.87	0.96	1.43	−0.13	−0.05	0.11
	1–10			−2.10	0.79	0.32	0.04	0.52	0.27	0.01
					(3.51)	(1.57)	(0.13)	(2.86)	(1.56)	(0.06)
3	1	109	61	−0.53	1.67	1.30	1.58	0.39	0.04	0.15
(High)	10	109	64	0.56	0.94	0.95	1.29	−0.11	−0.08	−0.09
	1–10			−1.09	0.73	0.35	0.28	0.50	0.13	0.24
					(4.34)	(2.12)	(1.64)	(3.55)	(0.85)	(1.75)
1–3	1–10			−2.01	0.56	0.86	0.39	0.63	0.96	0.21
					(1.73)	(2.66)	(1.18)	(2.06)	(2.80)	(0.65)

Panel C: Sorts by exchange ranked turnover, then SSTT

					% Raw returns, $K =$			% Adj. returns, $K =$		
Turnover group	SSTT portfolio	nStk	NYSE szRnk	SSTT	1–12	13–24	25–36	1–12	13–24	25–36
1	1	108	49	−0.46	1.20	1.43	1.46	−0.03	0.19	0.08
(Low)	10	109	65	0.35	1.19	1.05	1.19	0.05	−0.03	−0.16
	1–10			−0.80	0.01	0.38	0.27	−0.08	0.22	0.24
					(0.03)	(1.96)	(1.33)	(−0.48)	(1.15)	(1.21)
2	1	145	65	−0.81	1.53	1.17	1.48	0.20	0.01	0.07
	10	145	72	0.75	0.95	0.83	1.16	−0.22	−0.31	−0.07
	1–10			−1.56	0.58	0.34	0.33	0.42	0.31	0.14
					(2.71)	(1.71)	(1.40)	(2.60)	(1.73)	(0.71)
3	1	108	66	−1.11	1.72	1.60	1.70	0.53	0.52	0.36
(High)	10	109	61	2.31	0.46	0.73	1.39	−0.63	−0.21	0.28
	1–10			−3.42	1.25	0.87	0.31	1.15	0.73	0.08
					(4.44)	(3.58)	(1.15)	(4.95)	(3.05)	(0.33)
1–3	1–10			2.62	−1.25	−0.49	−0.04	−1.23	−0.51	0.16
					(−3.82)	(−1.63)	(−0.11)	(−4.60)	(−1.88)	(0.52)

Table 4
(Continued)

Panel D: Sorts by book-to-market value of equity, then SSTT

BM group	SSTT portfolio	nStk	NYSE szRnk	SSTT	% Raw returns, $K =$ 1–12	13–24	25–36	% Adj. returns, $K =$ 1–12	13–24	25–36
1	1	91	69	−0.67	1.74	1.49	1.43	0.57	0.39	0.09
(Low)	10	92	65	1.81	0.48	0.79	1.60	−0.50	−0.09	0.36
	1–10			−2.48	1.25	0.71	−0.16	1.07	0.48	−0.27
					(4.28)	(2.54)	(−0.47)	(4.17)	(1.99)	(−0.95)
2	1	122	67	−0.79	1.53	1.35	1.50	0.28	0.16	0.25
	10	123	70	0.97	0.78	0.83	1.19	−0.36	−0.30	−0.13
	1–10			−1.76	0.75	0.52	0.31	0.64	0.47	0.38
					(4.16)	(2.71)	(1.37)	(3.87)	(2.65)	(1.80)
3	1	91	67	−1.02	1.66	1.34	1.56	0.23	0.11	0.18
(High)	10	92	66	0.95	1.11	1.01	1.07	−0.17	−0.17	−0.23
	1–10			−1.97	0.54	0.34	0.49	0.40	0.28	0.41
					(2.22)	(1.27)	(1.94)	(1.97)	(1.22)	(1.73)
1–3	1–10			−0.51	0.71	0.37	−0.65	0.66	0.20	−0.68
					(2.17)	(1.01)	(−1.53)	(2.50)	(0.67)	(−1.84)

Panel E: Sorts by $ret_{-5:0}$ (momentum), then SSTT

Return group	SSTT portfolio	nStk	NYSE szRnk	SSTT	% Raw returns, $K =$ 1–12	13–24	25–36	% Adj. returns, $K =$ 1–12	13–24	25–36
1	1	109	53	−0.90	1.11	1.36	1.82	0.11	0.16	0.29
(Low)	10	109	64	1.50	0.35	1.16	1.87	−0.56	−0.01	0.46
	1–10			−2.40	0.76	0.20	−0.04	0.67	0.17	−0.16
					(2.75)	(0.73)	(−0.16)	(2.69)	(0.69)	(−0.67)
2	1	145	70	−0.71	1.48	1.42	1.48	0.24	0.22	0.14
	10	146	77	0.83	0.77	0.89	1.33	−0.30	−0.21	0.02
	1–10			−1.54	0.71	0.53	0.16	0.53	0.43	0.12
					(3.94)	(2.85)	(0.83)	(3.39)	(2.46)	(0.78)
3	1	109	68	−0.97	1.78	1.44	1.49	0.48	0.37	0.22
(High)	10	109	63	1.55	0.96	0.39	0.88	−0.22	−0.48	−0.17
	1–10			−2.51	0.82	1.05	0.61	0.70	0.85	0.39
					(2.91)	(4.53)	(2.19)	(3.26)	(4.01)	(1.69)
1–3	1–10			0.11	−0.06	−0.85	−0.65	−0.03	−0.68	−0.55
					(−0.19)	(−2.85)	(−2.16)	(−0.11)	(−2.26)	(−1.87)

Panel F: Sorts by $ret_{-41:-6}$ (three-year past returns), then SSTT

Return group	SSTT portfolio	nStk	NYSE szRnk	SSTT	% Raw returns, $K =$ 1–12	13–24	25–36	% Adj. returns, $K =$ 1–12	13–24	25–36
1	1	82	62	−1.27	1.62	1.39	1.49	0.33	0.22	0.19
(Low)	10	82	58	1.30	0.96	0.79	1.13	−0.19	−0.41	−0.09
	1–10			−2.57	0.66	0.60	0.36	0.52	0.63	0.28
					(2.72)	(2.37)	(1.44)	(2.59)	(2.87)	(1.16)
2	1	110	75	−0.65	1.65	1.32	1.36	0.31	0.17	0.07
	10	110	77	0.83	1.04	1.14	1.15	−0.17	−0.10	−0.20
	1–10			−1.48	0.61	0.18	0.22	0.47	0.27	0.27
					(3.25)	(1.04)	(1.19)	(2.73)	(1.56)	(1.61)
3	1	82	67	−0.59	1.50	1.51	1.51	0.24	0.46	0.19
(High)	10	82	71	1.37	0.78	1.07	1.51	−0.25	0.11	0.29
	1–10			−1.96	0.71	0.43	−0.00	0.50	0.35	−0.10
					(2.82)	(1.80)	(−0.01)	(2.12)	(1.61)	(−0.38)
1–3	1–10			−0.61	−0.06	0.17	0.36	0.03	0.28	0.38
					(−0.19)	(0.49)	(0.94)	(0.09)	(0.91)	(1.03)

Table 4
(Continued)

Panel G: Sorts by Exchange, then SSTT

Exchange	SSTT portfolio	nStk	NYSE szRnk	SSTT	% Raw returns, K = 1–12	13–24	25–36	% Adj. returns, K = 1–12	13–24	25–36
NYSE/	1	177	77	−0.61	1.33	1.24	1.43	0.13	0.05	0.16
AMEX	10	177	78	0.92	0.84	0.78	1.07	−0.31	−0.31	−0.24
	1–10			−1.54	0.49	0.46	0.36	0.44	0.36	0.40
					(2.18)	(2.11)	(1.52)	(2.54)	(2.04)	(2.16)
NASDAQ	1	242	50	−1.10	1.97	1.66	1.69	0.87	0.81	0.39
	10	243	56	1.74	0.64	0.67	1.80	−0.11	0.08	0.70
	1–10			−2.83	1.33	0.99	−0.11	0.98	0.73	−0.31
					(4.13)	(3.06)	(−0.30)	(3.80)	(2.70)	(−1.06)
NYSE/AMEX−	1–10			1.39	−0.82	−0.56	0.43	−0.49	−0.36	0.68
NASDAQ					(−2.62)	(−1.52)	(1.52)	(−1.68)	(−1.05)	(2.29)

Portfolios are formed monthly from June 1983 to January 2001 based on a stock characteristic (as indicated in the table headings), and within each characteristic portfolio, deciles are formed based on prior six-month SSTT ($J = 6$). The sample consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price ≥ \$5. Three portfolios are formed using 30% and 70% cut-off points of the characteristic, except in Panel F, which sorts by stock exchange. FVI6 is the fraction of trading volume over the prior six months that can be attributed to institutions via changes in 13f reports. $ret_{-5:0}$ is the return during the six-month formation period. $ret_{-41:-6}$ is the prior three-year return. *nStk* is the average number of stocks in the portfolio. *SzRnk* is the time-series average of the value-weighted mean NYSE percentage size rank of the stocks in the portfolio. The table presents the average monthly value-weighted returns of the low and high SSTT portfolios computed over holding period K. For instance, $K = 1$–12 represents average returns in months 1–12 after the portfolio formation, computed by averaging the current month's return of the strategies initiated over the prior 12 months. The adjusted returns are computed by subtracting the returns of a matched portfolio based on size, industry-adjusted BM ratios, and momentum quintiles from the monthly returns of each individual stock. t-statistics are in parentheses.

changes in (stock split-adjusted) holdings in number of shares, $\text{HOLD}_{j,q}$, at the end of each quarter, q:

$$\text{INSTVOL}_{i,q} = \sum_{j=1}^{J} |\text{HOLD}_{i,j,q-1} - \text{HOLD}_{i,j,q}|. \tag{1}$$

$\text{INSTVOL}_{i,q}$ is the number of shares traded in stock i during quarter q that can be directly traced to institutions. To match the length of the formation period for SSTT, six-month institutional trading volume is computed and then divided by the total trading volume to produce the fraction of trading volume attributable to institutions:

$$\text{FVI6}_{i,q} = \frac{\text{INSTVOL}_{i,q-1} + \text{INSTVOL}_{i,q}}{\text{VOL6}_{i,q}}, \tag{2}$$

where VOL6 is the (stock split-adjusted) number of shares traded during the six-month period obtained from the CRSP data.[11]

[11] Shu (2006) constructs this measure using quarterly volume and shows that stocks with a low fraction of volume attributable to institutions tend to have lower returns than those with a high fraction. He also finds that a number of return anomalies are stronger among stocks with a low fraction. Shu reports the distribution of institutional trading volume and finds that on average 54% of total volume is attributable to institutions. I find a similar distribution among the NYSE/AMEX firms in the current sample.

At the end of each quarter, stocks are ranked within NYSE/AMEX and NASDAQ separately according to FVI6, and all stocks are sorted according their rank FVI6 into three portfolios using cut-off points at 30% and 70%. Within each rank FVI6 portfolio, stocks are then sorted monthly into SSTT deciles. All else equal, retail trading constitutes a high fraction of volume in stocks where FVI6 is low, and therefore we would expect a larger effect of SSTT among such stocks.

The results reported in Panel B of Table 4 are consistent with the hypothesis. Among the stocks with the lowest fraction of trading volume attributable to institutions, the return difference across the SSTT deciles is very large and persistent: the characteristic-adjusted return difference is 1.13% per month in the first year (t-statistic = 4.08), 1.09% per month in the second year (t-statistic = 3.65), and an insignificant 0.46% in the third year (t-statistic = 1.46). The raw returns are similarly large, and the raw return difference remains significant in the third year. The corresponding zero-investment returns among stocks in the high institutional trading group is considerably lower at 0.50% and 0.13% per month in the first and second year, respectively. The differences of 0.63% and 0.96% are significant at the 5% level. That is, the profitability of the SSTT portfolios is significantly higher in stocks where a larger proportion of the trading volume appears to originate from retail investors.

To further investigate the effect of SSTT, Panels C–G in Table 4 show the returns to SSTT portfolios within portfolios based on turnover during the six-month formation period, BM, six-month momentum, returns over the three years prior to the formation period, and stock exchange. Panel C shows that the relationship between SSTT and future returns is muted among low-turnover stocks, but very strong among high-turnover stocks. For instance, the characteristic-adjusted return differential is 1.15% per month in the first year (t-statistic = 4.95) among the high-turnover stocks. Panel C shows the results within BM portfolios. The BM effect has been linked to overvaluation (e.g., Lakonishok, Shleifer, and Vishny, 1994; and Daniel and Titman, 2006), hence one might expect SSTT to have a stronger relationship with future returns among low BM stocks. Indeed, the table shows that return differences are higher among low BM stocks, with a characteristic-adjusted return differential of 1.07% per month in the first year (t-statistic = 4.17) among those stocks. The results in Panel E suggests that no differences in profitability exist across momentum portfolios in the first year. However, the return differences appear to be more persistent among winners, as the zero-investment portfolio continues to be profitable in years 2 and 3 among winners, but not among losers. The prior long-term returns are included in Panel F, because one might suspect that, because SSTT is highly correlated with past three-year returns, the SSTT result is simply a restatement of the De Bondt and Thaler (1985) long-term reversal finding. However, the SSTT continues to predict future returns within all three long-term return portfolios. Finally, Panel G shows that initial return differences tend to be higher among NASDAQ stocks, but the return differences also exist and indeed persist up to three years among NYSE/AMEX stocks.

3.2 Seasonality of returns

Hvidkjaer (2006) finds a distinct seasonality in small-trade imbalances among winners and losers. For instance, a strong selling pressure exists among losers in December, consistent with individuals realizing losses for tax purposes at the end of the year. To the extent that year-end tax-loss selling by individuals affect returns in January, at least three effects could be observed in the current data. First, we would expect any January effect to be most pronounced for short formation and holding periods, since returns over longer horizons are based on SSTT measured over the entire year. Secondly, absent substitution effects, we would expect the zero-investment returns in January to arise from the long side, namely the portfolio with selling pressure in December. Thirdly, since tax-loss selling mainly is beneficial to individuals, we would expect any January effect to be most pronounced among stocks in which individuals constitute a large fraction of the trader population. The results presented below are consistent with these predictions.

Table 5 analyzes the return seasonality of two strategies: a short-term strategy with one-month formation period and one-month holding period ($J = 1, K = 1$), and the longer-term strategy with $J = 6, K = 2 - 7$. In Panel A, stocks are sorted into deciles by SSTT. The first return column shows the average monthly returns using the full sample, and the next three columns split that into returns in January, December, and the rest of the year, respectively. For the $J = 1, K = 1$ strategy, the composition of the January portfolio depends on SSTT in December, while for the $J = 6$, $K = 2 - 7$ strategy, the composition of the January portfolio depends on SSTT in the preceding January through November (because January returns are based on portfolios formed in June through November).

Focusing on the characteristic-adjusted returns in Table 5, we see that the zero-investment portfolio returns are 2.33% in January (t-statistic = 2.50), substantially higher than the 0.67% return during February to November. For the $J = 6, K = 2 - 7$ strategy, however, there is little evidence of seasonality in the returns to the zero-investment portfolio, with 0.95% return in January compared to 0.64% during February to November. Indeed, the raw returns of the zero-investment portfolio are lower in January than during February to November. Moreover, the return differential in January for the $J = 1$, $K = 1$ strategy entirely accrues from the low SSTT portfolio, which outperforms its benchmark portfolio by 2.51% (t-statistic = 2.62). By contrast, the low SSTT portfolio has an average adjusted return of only 0.06% per month (t-statistic = 0.35) during February to November, and the returns to the zero-investment portfolio accrues from the negative returns to the high SSTT portfolio.

December returns were separated based on the reasoning that if tax-loss selling appears in November, then the same stocks would likely see more tax-loss selling in December, creating a further downward pressure on prices. Also, Grinblatt and Moskowitz (2004) show that a December effect exists in the returns of momentum portfolios, consistent with the price pressure hypothesis.

Table 5
Seasonality of returns

Form./hold. period	FVI3 group	SSTT portfolio	% Raw returns All year	Jan	Dec	Feb–Nov	% Adj. returns All year	Jan	Dec	Feb–Nov
Panel A: Univariate sorts by SSTT										
$J = 1, K = 1$		1	1.54	6.71	2.04	0.98	0.18	2.51	−1.00	0.06
							(0.97)	(2.62)	(−1.60)	(0.35)
		10	0.79	3.46	3.74	0.23	−0.47	0.19	0.14	−0.60
							(−2.42)	(0.59)	(0.20)	(−2.72)
		1–10	0.75	3.25	−1.70	0.75	0.65	2.33	−1.14	0.67
			(2.45)	(1.82)	(−1.57)	(2.53)	(2.72)	(2.50)	(−1.29)	(2.62)
$J = 6, K = 2–7$		1	1.59	5.32	3.35	1.04	0.34	2.05	0.10	0.19
							(2.20)	(2.39)	(0.16)	(1.30)
		10	0.71	4.67	2.17	0.18	−0.35	1.09	−0.83	−0.45
							(−1.88)	(1.51)	(−1.41)	(−2.22)
		1–10	0.87	0.66	1.18	0.87	0.69	0.95	0.93	0.64
		(3.59)	(0.86)	(1.65)	(3.16)		(3.58)	(1.58)	(1.15)	(3.05)
Panel B: Sorts by exchange ranked FVI3 (institutional trading), then SSTT										
$J = 1, K = 1$	1	1	1.22	9.63	−0.35	0.54	−0.12	5.40	−2.95	−0.39
	(Low)						(−0.37)	(3.66)	(−3.17)	(−1.23)
		10	0.12	4.20	2.71	−0.54	−1.20	0.49	0.07	−1.50
							(−3.42)	(0.55)	(0.04)	(−4.08)
		1–10	1.09	5.43	−3.06	1.08	1.08	4.91	−3.02	1.11
			(2.48)	(2.58)	(−1.50)	(2.54)	(2.68)	(3.02)	(−1.50)	(2.83)
	3	1	1.20	3.43	2.13	0.89	−0.17	−0.11	−0.89	−0.11
	(High)						(−1.21)	(−0.17)	(−1.29)	(−0.75)
		10	1.59	3.03	5.43	1.06	0.24	0.05	1.31	0.15
							(1.52)	(0.10)	(2.75)	(0.87)
		1–10	−0.38	0.40	−3.30	−0.17	−0.41	−0.16	−2.20	−0.26
			(−1.36)	(0.29)	(−2.21)	(−0.65)	(−1.93)	(−0.17)	(−2.30)	(−1.20)
	1–3	1–10	1.48	5.03	0.24	1.25	1.49	5.08	−0.82	1.37
		(3.80)	(3.24)	(0.14)	(3.13)	(3.68)	(3.17)	(−0.52)	(3.23)	

Deciles are formed monthly from January 1983 to January 2001 based on prior J-month SSTT, and the sample consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price $\geq$ \$5. Stocks with low (high) SSTT are in decile 1 (10), and returns are value-weighted within deciles. The table presents the average monthly raw and characteristic-adjusted returns computed over holding periods K. In Panel B, stocks are first sorted into three portfolios according to FVI3, the fraction of trading volume over the prior three months that can be attributed to institutions via changes in 13f reports. Returns are shown for SSTT portfolios created within the bottom and top 30% of FVI3. Returns are adjusted by subtracting the returns of a matched portfolio based on size, industry-adjusted BM ratios, and momentum quintiles from the monthly returns of each individual stock. The difference in returns between the low and the high SSTT portfolios are also reported, along with t-statistics in parentheses.

Indeed, the average adjusted return in December for the low SSTT portfolio is −1.00%, although it is insignificant with a t-statistic of −1.60.

Panel B of Table 5 shows the $J = 1, K = 1$ returns to SSTT portfolios within portfolios based on FVI6three, the fraction of trading volume over the prior quarter attributable to institutions. That is, INSTVOL is computed as in Equation (1) and divided by the number of shares traded over the quarter. As before, the fraction is ranked within NYSE/AMEX and NASDAQ separately. The table shows the results based on the stocks with the 30% lowest institutional trading and for comparison also shows the results based on the stocks with the 30% highest institutional trading. As predicted above, the results for the low institutional trading stocks are stronger than those reported in Panel A. For instance, the low SSTT portfolio yields 5.40% adjusted returns in January (t-statistic = 3.66), but −2.95% in December (t-statistic = −3.17). The overall return differential between the low and high SSTT portfolios is 1.08% per month (t-statistic = 2.68), similar to the results for longer holding periods shown in Table 4 Panel B. Among the stocks with a high fraction of volume attributable to institutions, the returns to the zero-investment portfolio are generally negative, and there is little evidence of a January effect, although December returns are significantly negative.[12]

3.3 Returns in the post decimalization period

Section 2 showed evidence that institutions increasingly engage in order-splitting strategies resulting in more small trades originating from large institutional investors. If the return predictability in SSTT in fact is driven by retail investor behavior, then we would expect this predictability to diminish in the final years of the sample. The splitting of large orders into small trades was arguably in part driven by the shift to decimal pricing in 2001. The NYSE and AMEX completed the decimalization in January 2001, while NASDAQ completed its conversion to decimal pricing in April 2001. Therefore, SSTT data beginning in May 2001 were used to construct portfolios in the post decimalization period. Since trade and return data are available through 2005, less than five years of return data are available, and therefore only shorter-term strategies are considered. Table 6 shows the returns to SSTT deciles based on formation periods of 1, 3 and 6 months, and holding periods up to one year. Most of the returns to the zero-investment portfolio are positive but relatively low and insignificant. The highest level of significance is achieved for the $J = 3$, $K = 1$ strategy, in which the low SSTT portfolio outperforms the high SSTT portfolio by 0.69% per month (t-statistic = 1.84) using the characteristic-adjusted returns. However, this return spread is not robust to changes in either J or K, as for example the $J = 6$, $K = 1$ strategy only yields 0.18% per month and the $J = 3$, $K = 2 - 7$ strategy yields −0.04% per month. Also, the returns of portfolios 2 and 9 do not suggest any predictive power of SSTT: the raw returns of portfolio 2 are higher than those of portfolio 9 in only two of the nine strategies in Table 6, while the adjusted returns are higher in five of the nine strategies. Overall, the short sample period makes it difficult to make firm conclusions about the power of SSTT to explain returns in the post decimalization period, but the return spread does appear to be lower than in the main sample.

Figure 2 provides another perspective on the returns throughout the full sample sample period 1983–2005. The figure depicts the year-to-year returns of the $J = 6$, $K = 2 - 7$ strategy. Using raw returns, Figure 2(a) shows that the strategy yields negative returns in six of the 23 years, with a maximum loss

[12] Although the institutional trading volume is from the quarter prior to the holding period, this information is not available to investors until a few months later. Therefore, the short-term strategies in Table 5 that are based on institutional trading volume are not directly implementable.

Table 6
Returns in the post decimalization period

		% Raw returns, K =			% Adj. returns, K =		
Formation period	portfolio	1	2–7	1–12	1	2–7	1–12
$J = 1$	1	0.65	0.73	0.78	0.01	−0.08	−0.02
	2	0.71	0.55	0.49	0.08	0.12	0.11
	9	0.22	0.60	0.60	−0.26	−0.14	−0.07
	10	−0.07	0.19	0.18	−0.62	−0.39	−0.38
	1–10	0.73	0.54	0.60	0.63	0.31	0.37
		(1.65)	(1.01)	(1.40)	(1.62)	(0.65)	(0.97)
$J = 3$	1	0.77	0.92	0.95	0.22	−0.07	0.13
	2	0.17	0.41	0.06	−0.15	−0.24	−0.48
	9	0.57	0.87	0.82	−0.16	−0.10	0.03
	10	0.13	0.77	0.48	−0.47	−0.03	−0.14
	1–10	0.63	0.15	0.47	0.69	−0.04	0.27
		(1.47)	(0.34)	(1.08)	(1.84)	(−0.11)	(0.80)
$J = 6$	1	0.85	0.92	1.11	−0.08	0.07	0.12
	2	0.69	0.10	0.40	−0.02	−0.55	−0.49
	9	0.92	0.83	1.06	−0.08	−0.08	−0.01
	10	0.76	0.53	0.91	−0.26	−0.17	−0.07
	1–10	0.10	0.39	0.20	0.18	0.24	0.18
		(0.26)	(1.08)	(0.57)	(0.54)	(0.71)	(0.64)

Deciles are formed monthly from May 2001 to November 2005 based on prior J-month SSTT, and the sample and consists of all NYSE/AMEX/NASDAQ stocks with a price ≥$5. Stocks with low (high) SSTT are in decile 1 (10), and returns are value-weighted within deciles. The table presents the average monthly raw and characteristic-adjusted returns computed over holding periods K. Returns are adjusted by subtracting the returns of a matched portfolio based on size, industry-adjusted BM ratios, and momentum quintiles from the monthly returns of each individual stock. The difference in returns between the low and the high SSTT portfolios are also reported, along with t-statistics in parentheses.

of 16.5% in 1991, while profits are at least 10% in 12 of the sample years. The characteristic-adjusted returns in Figure 2(b) show a similar pattern, although the returns are lower and less volatile. The main difference between the raw and characteristic-adjusted returns appears in the 1998–2001 period: the adjustment increases the 1998–1999 returns, but reduces the high profitability in 2000–2001. In the postdecimalization period, returns are negative in two of the five years, but large and positive in the remaining three years. However, further analysis shows that the positive returns in 2001 entirely accrues from the first half of the year, which uses SSTT data prior to the decimalization.

3.4 Time-series regressions

In order to analyze the systematic risk of the SSTT portfolio returns and to provide an alternative risk adjustment of returns, this section examines the returns using the Fama-French three-factor model. Fama and French (1993) find that the returns on three-factor-mimicking portfolios, constructed as the overall stock market portfolio (r_m), a portfolio long small firms and short large firms (SMB), and a portfolio long firms with high ratio of book-to-market value of equity and short low BM firms (HML), seem to explain average returns to stock portfolios.

Table 7 performs time-series regressions, similar to Fama and French (1993). First, the portfolio excess returns of the $J = 6$, $K = 2$–7 value-weighted

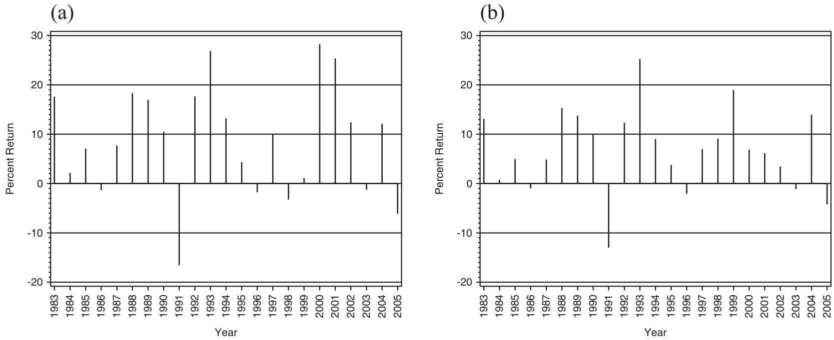

Figure 2
Yearly return differences between low and high SSTT portfolios
Deciles are formed monthly in 1983–2005 based on past six-month SSTT. The figures present the yearly difference between the returns of low and high SSTT portfolios using a six-month holding period ($K = 2 - 7$). The first formation month is June 1983, so that year only contains the returns from the last five months. Figure 2(a) presents the difference in the raw returns, and Figure 2(b) presents the difference in the characteristic-adjusted returns (based on size, BM, and momentum).

strategy are regressed against r_m, the CRSP value-weighted NYSE/AMEX/NASDAQ index excess returns. The β_{r_m} coefficients do not indicate that beta risk can account for the return differential between the low and high SSTT portfolios. On the contrary, the high SSTT portfolio has by far the highest beta coefficient at 1.49, but since the strategy is short in that portfolio, the zero-investment portfolio has a negative beta of -0.42. Correspondingly, the intercept of the regression with the zero-investment portfolio is, at 1.15 (t-statistic = 5.43), higher than the average raw return of 0.94% reported in Table 2. Secondly, the portfolio returns are regressed against the three Fama-French factors. This does reduce the intercept to 0.84, but it remains highly significant with a t-statistic of 4.24. Interestingly, both the low and the high SSTT portfolio seem to have a stronger covariation with growth firms than suggested by their BM ratios in Table 1. Concretely, the coefficient on HML is insignificant for the low SSTT portfolio, even though Table 1 shows a high BM ratio for that portfolio. Likewise, even though the BM ratio of the high SSTT portfolio is not lower than those of the preceding three portfolios, the loading of that portfolio on HML is strongly negative.

The loadings on the SMB returns exhibit a marked U-shaped pattern across SSTT portfolios. That is, the low and high SSTT portfolios have strongly positive loadings, while intermediate portfolios have negative loadings. In other words, the extreme SSTT stocks tend to have high covariation with small firms, even though the value-weighting ensures that the returns of those portfolios are mainly driven by large stocks.[13] Because both the low and high SSTT portfolios have high levels of small-trade turnover, and therefore are likely to have a high

[13] Table 1 showed that the stocks in the extreme SSTT portfolios are somewhat smaller than those in the intermediate portfolios, which makes inference about the relative loadings more difficult. However, additional analysis using double sorts on size and SSTT shows that the U-shape is present in all size quintiles.

Table 7
Time-series regressions

	Low	2	3	4	5	6	7	8	9	High	Low–High
Market factor											
α	0.40	0.46	0.32	0.30	0.22	0.04	0.04	−0.06	−0.25	−0.74	1.15
	(2.07)	(3.92)	(3.64)	(3.27)	(2.09)	(0.36)	(0.43)	(−0.64)	(−2.28)	(−3.11)	(5.43)
β_{rm}	1.08	0.95	0.92	0.84	0.87	0.92	1.02	1.09	1.19	1.49	−0.42
	(24.79)	(36.26)	(47.25)	(40.66)	(37.60)	(38.35)	(47.83)	(53.77)	(48.47)	(27.96)	(−8.80)
Adj. R^2	0.74	0.86	0.91	0.88	0.87	0.87	0.91	0.93	0.92	0.78	0.26
Fama-French three-factor											
α	0.54	0.40	0.17	0.12	0.01	−0.09	0.03	−0.04	−0.08	−0.30	0.84
	(3.34)	(3.74)	(2.17)	(1.56)	(0.16)	(−0.99)	(0.36)	(−0.44)	(−0.80)	(−1.64)	(4.24)
β_{rm}	1.00	1.00	1.01	0.95	1.00	1.00	1.02	1.08	1.08	1.23	−0.23
	(23.83)	(36.22)	(49.13)	(48.34)	(47.05)	(42.63)	(48.78)	(48.13)	(40.89)	(25.49)	(−4.39)
β_{SMB}	0.48	0.28	0.06	−0.04	−0.11	−0.21	−0.26	−0.18	−0.02	0.34	0.15
	(9.28)	(8.23)	(2.33)	(−1.74)	(−4.07)	(−7.22)	(−9.92)	(−6.43)	(−0.74)	(5.59)	(2.32)
β_{HML}	−0.04	0.20	0.24	0.26	0.27	0.12	−0.07	−0.09	−0.26	−0.54	0.51
	(−0.58)	(4.79)	(7.83)	(8.94)	(8.53)	(3.42)	(−2.28)	(−2.77)	(−6.60)	(−7.58)	(6.59)
Adj. R^2	0.83	0.89	0.93	0.93	0.92	0.92	0.94	0.94	0.93	0.88	0.38
Fama-French three-factor + UMD											
β_{UMD}	−0.12	−0.08	−0.01	0.00	−0.04	−0.16	−0.13	−0.14	−0.08	−0.23	0.11
	(−3.22)	(−3.23)	(−0.46)	(0.10)	(−2.05)	(−8.71)	(−7.99)	(−7.80)	(−3.57)	(−5.59)	(2.34)
Fama-French three-factor + PIN											
β_{PIN}	−0.49	−0.38	−0.16	0.00	0.01	−0.06	−0.04	−0.17	−0.06	−0.54	0.05
	(−4.13)	(−5.00)	(−2.64)	(0.03)	(0.23)	(−0.91)	(−0.73)	(−2.70)	(−0.76)	(−3.98)	(0.35)

Deciles are formed monthly based on prior six-month SSTT ($J = 6$), and value-weighted portfolio returns are computed using a six-month holding period ($K = 2$–7). The table presents selected statistics from regressing the portfolio excess returns on the Fama-French factors: market excess return (r_m), small stock returns minus large stock returns (SMB), high book-to-market stock returns minus low book-to-market stock returns (HML), and past one-year winner stock returns minus past loser stock returns (UMD). In addition, regressions are performed including the PIN factor, which is the difference between the monthly returns of a high and a low PIN portfolio, where PIN is a measure of the probability of information-based trading in a stock. The estimation of PIN and the PIN portfolio construction are detailed in Easley, Hvidkjaer, and O'Hara (2005). The sample covers January 1983 to January 2001, and consists of all NYSE/AMEX and (beginning 1987) NASDAQ stocks with a price $\geq$ \$5. t-statistics are in parentheses.

degree of retail investor participation, the results are consistent with the hypothesis that excess comovements exist among stocks with high retail investor participation (see Lee, Shleifer, and Thaler, 1991; and Kumar and Lee, 2006).

Table 7 also shows the loadings on the momentum factor (UMD). Both the low and the high SSTT portfolios load negatively on UMD, and the loading of 0.11 for the zero-investment portfolio, while positive, is economically small. Finally, Table 7 includes results from adding the factor-mimicking returns based on PIN, suggested by Easley, Hvidkjaer, and O'Hara (2005). PIN is an estimate of the probability that a given trade is motivated by private information (see Easley, Hvidkjaer, and O'Hara, 2002). Because small and large trades are likely to have different information content, the profitability of SSTT could be related to PIN. In fact, both the low and the high SSTT portfolios have large negative loadings on the PIN factor, while the intermediate portfolios tend to have low loadings. This is consistent with the observation in Table 1 that both the low and high SSTT portfolios have high levels of small-trade volume, which is likely less informed than larger trades. Moreover, the loadings of the two portfolios are almost identical, leaving PIN unable to explain the returns to the zero-investment portfolio.[14]

4. Conclusion

The results in this paper show that small-trade volume contains information about the cross-section of future stock returns. Concretely, stocks with a high level of sell-initiated small-trade volume, measured over the prior several months, outperform stocks with a high level of buy-initiated small-trade volume. The return difference is economically large and statistically significant at least two years in the future. The results suggest that stocks favored by retail investors tend to experience large and prolonged underperformance in the future, relative to stocks out of favor with retail investors.

While the results link the systematic component of retail investor behavior to future returns, this relationship could arise through different mechanisms. In one possible mechanism, retail investors actively push prices away from fundamentals with their trades and prices revert to fundamentals over time. Thus, there is no information about fundamentals in their trades, but the fact that individuals are trading in a coordinated fashion in a particular stock is itself information. In another possible mechanism, informed investors might begin selling stocks that they believe to be overvalued. The overvaluation that these investors perceive could be driven by changes in firms' fundamental values. Retail investors notice falling prices and purchase the stocks for prices that appear to them to be below intrinsic values. In this case, the retail investors do not cause the initial mispricing, but rather facilitate the mispricing.[15] The hope is that future research will be able to disentangle such alternative mechanisms.

Appendix: 1993 Turnover by Exchange

It is well known that reported trading volume on NASDAQ is inflated relative to the NYSE and AMEX due to the double-counting of trades in multiple dealer markets. Signed volume measures would be expected to be inflated by a similar amount. However, it is less obvious that small-trade volume would be inflated on NASDAQ to a similar degree. For instance, inter dealer trading, which creates much of the double-counting, is presumably concentrated in larger trade sizes. Also, the specialist on the NYSE is probably more likely to act as a dealer in smaller trades than in overall volume, in part because the specialist only acts a broker in the upstairs market for block trades, which constitutes a large proportion of NYSE volume over the sample period. To assess whether small-trade volume is inflated on NASDAQ, I compared the relative volume of NASDAQ versus NYSE/AMEX in 1993, which is the first year of the TAQ data. In the table below, stocks were sorted into size deciles and then grouped by exchange. The table shows the average total turnover and small-trade turnover for each

[14] In addition to the time-series regressions, cross-sectional Fama-MacBeth regressions controlling for size, BM, momentum, and long-term returns were estimated. The results were not materially different from those reported in the main text.

[15] I am grateful to a referee for pointing out these alternative mechanisms.

exchange, along with the differences between the exchanges. The table also reports the Wald test for equality of turnover across deciles. For the differences column, the Wald statistic tests whether differences are jointly equal to zero. The double-counting of volume is clear when comparing turnover based on all trades, with NASDAQ turnover being substantially larger than NYSE/AMEX turnover across all size deciles. By contrast, NASDAQ small-trade turnover is only larger than that of the NYSE/AMEX in six of the ten size portfolios, though the Wald tests rejects that the differences are jointly zero. Interestingly, NASDAQ small-trade turnover is almost constant across size deciles, but NYSE/AMEX small-trade turnover is larger for small stocks than for large stocks. This is consistent with the specialist more often providing liquidity as a dealer in small stocks to small trades, while matching such trades in larger stocks.

	Total turnover (%)			Small-trade turnover (%)		
Size	NASDAQ	NYSE/AMEX	Difference	NASDAQ	NYSE/AMEX	Difference
Small	87.4	59.5	27.9	5.15	6.03	−0.88
2	98.2	59.3	38.8	4.23	5.00	−0.77
3	111.1	50.1	61.0	5.02	4.67	0.35
4	117.6	63.3	54.3	5.08	5.55	−0.47
5	140.4	78.1	62.4	4.72	5.44	−0.72
6	151.4	75.5	75.9	5.84	4.85	0.98
7	160.4	73.8	86.6	4.68	4.45	0.22
8	187.6	75.8	111.9	5.29	3.96	1.33
9	231.1	75.7	155.4	5.24	3.93	1.30
Large	174.0	68.1	105.9	4.78	3.30	1.48
Wald	126.5	29.2	415.8	12.62	60.96	24.09
p-value	(.000)	(.001)	(.000)	(.181)	(.000)	(.007)

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