A Trade-Based Analysis of Momentum

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This article uses transactions data for all NYSE/AMEX stocks in the period 1983–2002 to study how investors trade in Jegadeesh and Titman's (1993) momentum portfolios. Among small trades, there is an extremely sluggish reaction to the past returns. For instance, an initial small-trade buying pressure exists for loser stocks, and it gradually converts into an intense selling pressure over the following year. The results are consistent with initial underreaction followed by delayed reaction among small traders. Moreover, small-trade imbalances during the formation period significantly affect momentum returns, suggesting that underreaction among small traders contributes to the momentum effect. Large traders, by contrast, show no evidence of underreaction, and large-trade imbalances have little impact on subsequent returns. Overall, the results suggest that momentum could partly be driven by the behavior of small traders.

Jegadeesh and Titman (1993) document a pervasive momentum effect in stock returns at the 3- to 12-month horizons. The effect does not appear to be explained by existing rational asset pricing models, and it is robust, as the result holds out of sample, both in non-U.S. equity markets and after the original sample period.[1] As such, momentum represents a serious challenge to the market efficiency hypothesis, and a fundamental question is why does this return continuation arise?

Recent behavioral theories argue that momentum could be caused by naïve investors with biased expectations.[2] More generally, the literature on behavioral finance suggests that individuals use heuristics or suffer

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I benefited from the comments of Gurdip Bakshi, Nicholas Barberis, David Easley, David Hirshleifer, Yongmiao Hong, Zoran Ivković, Yaniv Grinstein, Campbell Harvey (the editor), Pal Korsvold, Charles Lee, Roni Michaely, Tobias Moskowitz, Maureen O'Hara, Andrea Pederzolli, Adam Reed, Gideon Saar, Bhaskaran Swaminathan, James Weston, and seminar participants at the AFA meetings, the Conference on Finance and Psychology in Mannheim, Cornell University, Emory University, the European Finance Association meetings, the Frank Batten Conference, George Washington University, HEC, London Business School, McGill University, Pennsylvania State University, UC-Davis, University of Chicago, UI Urbana-Champaign, University of Maryland, University of Notre Dame, Washington University, and the WFA meetings. I am especially grateful to an anonymous referee. Financial support from the Nasdaq Educational Foundation is gratefully acknowledged. Address correspondence to Soeren Hvidkjaer, R.H. Smith School of Business, 4428 Van Munching Hall, University of Maryland, College Park, MD 20742, or email: shvidkja@rhsmith.umd.edu.

[1] See, e.g., Chan, Jegadeesh, and Lakonishok (1996), Fama and French (1996), Fama (1998), Rouwenhorst (1998), Jegadeesh and Titman (2001), Grundy and Martin (2001), Griffin, Ji, and Martin (2003), Grinblatt and Moskowitz (2004), and Bhojraj and Swaminathan (2004).

[2] In Barberis, Shleifer, and Vishny (1998), *conservative* investors underreact to earnings news, while in Daniel, Hirshleifer, and Subrahmanyam (1998), *overconfident* investors overreact to private signals and underreact to public news. Hong and Stein (1999) model the underreaction as occurring when boundedly rational agents each observe some private information but fail to extract other agents' information from prices, resulting in a gradual diffusion of information.

doi:10.1093/rfs/hhj016 Advance Access publication January 20, 2006

from cognitive biases, leading them to hold particular models of risk and expected return. If the predictions of these models are uncorrelated across investors, people will trade with each other, but price effects would be minimal. However, when different models lead to similar predictions, investors will try to buy (or sell) the same securities at the same time, thereby driving prices up (or down) even in the absence of new fundamental information (Shleifer, 2000). In other words, the link between cognitive biases and prices is the actions or the trading behavior of investors. Therefore, we can study trading behavior to examine whether it is consistent with a proposed behavioral explanation of a return anomaly, or whether it is consistent with more rational motivations for trading.

Momentum is a natural starting point for such a study, since it is an especially simple strategy and past returns are likely to be a key signal on which investors focus. Momentum could be driven by initial underreaction or by a delayed reaction among investors. That is, it could be driven by initial buying pressure and/or delayed selling pressure among losers and initial selling pressure and/or delayed buying pressure among winners. This article tests these predictions by employing transactions data in all NYSE/AMEX stocks over the 1983–2002 period to analyze trade imbalances in momentum portfolios. Moreover, momentum provides an excellent opportunity to study how demand affects future returns. Specifically, since there is a well-defined period during which returns are measured to form momentum portfolios, we can examine whether trade imbalances during this formation period affect subsequent momentum returns.

Every trade is, of course, both a buy and a sell. However, market microstructure makes an important distinction between active and passive traders. Active traders demand immediacy by submitting market orders and, in turn, typically buy at a price above the quote midpoint and sell at a price below the midpoint. Passive traders provide immediacy either as market makers or by submitting limit orders. Prices respond primarily to the trade direction of the active trader, either because she is simply a liquidity consumer or because the trade reflects the possible existence of private information, as shown by Kyle (1985), Glosten and Milgrom (1985), and Easley and O'Hara (1987). Trade imbalances therefore refer to imbalances among active traders. If there is more seller- than buyer-initiated volume, I call it a selling pressure, while if there is more buyer- than seller-initiated volume, I call it a buying pressure.

All trades are classified as small or large trades based on firm-specific cut-off points for the dollar amount traded, and the trade imbalance measure is computed separately for small and large trades. Trade imbalances among small trades are likely to be correlated with the trading behavior of individual investors, while trade imbalances among large trades are more likely to reflect trading by institutional investors. Indeed, based on quarterly data, I find a positive (negative) correlation between changes in institutional holdings and large-trade (small-trade) imbalances. Institutions might be considered more sophisticated investors, and empirical evidence does indicate differences in trading behavior across size groups. For instance, Lee (1992) shows that small investors trade differently from large investors around earnings announcements, as a small-trade buying pressure appears after earnings announcements, independently of whether the news release was good or bad. Also, Odean (1998, 1999) and Barber and Odean (2000, 2002) show that individual investors seem to pursue relatively unsophisticated trading strategies.

I find that small and large traders exhibit quite distinct trading behavior. A small-trade buying pressure appears among losers in most of the six-month formation period of the momentum portfolios. The buying pressure becomes very strong on the formation date, but then a selling pressure gradually sets in, and it peaks almost a year later. Thus, among losers, the trade imbalances are consistent with initial underreaction followed by a delayed reaction by small investors. Evidence of a delayed reaction also exists among winners, as a small-trade buying pressure gradually emerges during the six months following the formation date. However, a small-trade buying pressure also appears during the formation period.

The analysis reveals a completely different trading behavior by large traders. A strong large-trade selling pressure appears among losers during the formation period. On the formation date, the selling pressure drops significantly and then gradually disappears over the following year. Winners exhibit a largely symmetric buying pressure. Thus, little evidence of initial underreaction or delayed reaction exists among large trades. On the contrary, the evidence is consistent with informed trading among large traders and suggests that the average large trader engages in (early-stage) momentum trading.[3]

By measuring the relative amount of buying and selling among small trades, the small-trade imbalance is a natural candidate as a measure of the extent to which small-investor sentiment is high in a stock at some point in time.[4] Lee and Swaminathan (2000) find an interaction between momentum and share turnover and suggest that also turnover provides information on the extent to which investor sentiment favors a stock at a particular point in time. If both small-trade imbalances and share turnover are sentiment indicators, we would expect the two measures to be

[3] This is consistent with findings based on quarterly changes in institutional holdings, as discussed in Section 2.4.

[4] The small-trade imbalance is similar to the ratio of odd-lot buys to sales, which has long been suggested as a measure of small investor sentiment. For instance, Gup (1973, p. 676) notes that the ratio is sometimes referred to as a "yardstick of uninformed sentiment." See also, e.g., Branch (1976), Shleifer and Summers (1990), and Neal and Wheatley (1998).

positively correlated. Indeed, I find that while little relation exists between formation-period turnover and small-trade imbalances among winners, a strong correlation appears among losers. That is, low-turnover losers exhibit a formation-period selling pressure, while high-turnover losers exhibit a strong formation-period *buying* pressure. This result is consistent with the findings in Lee and Swaminathan (2000) that high-turnover losers underperform low-turnover losers, while little difference exists in the returns of low- and high-turnover winners.

The trading pressures might partly explain the momentum anomaly, or they might be entirely inconsequential for returns. It is difficult to establish a causal link between the delayed reaction and momentum returns, since these occur simultaneously during the holding period. However, the evidence of initial small-investor underreaction among losers provides an opportunity to test whether the trading pressures translate into price pressures. Within momentum portfolios, I sort into portfolios based on formation-period trade imbalances and measure subsequent returns. The results show that losers with strong small-trade selling pressures significantly outperform losers with strong buying pressures. For instance, using a six-month formation period and a six-month holding period (skipping the first month after the portfolio formation date), the average difference between the characteristic-adjusted (based on size, book-to-market, and industry) returns of the two portfolios is 0.48% per month (*t*-statistics 3.28).

Moreover, the effect of small-trade imbalances on future returns is concentrated among high-turnover stocks. High-turnover losers with strong small-trade selling pressure outperform high-turnover losers with strong small-trade buying pressure by about 0.60% per month. A significant relationship between trade imbalances and future returns also exists among high-turnover winners. By contrast, the relation between trade imbalances and future returns is insignificant among low-turnover stocks. Reversing the sorting order, I find that the predictive power of turnover for future returns is concentrated among stocks with buying pressure, while the relationship between turnover and future returns among stocks with selling pressure is insignificant. This supports the notion that turnover could be an indicator about investor sentiment in a stock.

Grinblatt and Moskowitz (2004) find a linkage between momentum and the seasonality of returns, indicating that tax-motivated trading affects returns. Analysis shows that the trading pressures also exhibit a marked seasonality consistent with tax-motivated trading. For instance, losers show a year-end small-trade selling pressure followed by a January buying pressure. However, the results discussed above are not driven simply by tax-motivated or other seasonality-related trading, since the initial small-trade buying pressure and delayed selling pressure among losers are evident throughout the year.

The remainder of the article is organized as follows. Section 1 describes the data and the construction of the trade imbalance variables. Section 2 analyzes the event-time trade imbalances of the different momentum and momentum-turnover portfolios and examines the seasonality of the trade imbalances. Also, comparison is made with net institutional trading at the quarterly horizon to evaluate the extent to which small- and large-trade imbalances reflect net shifts in holdings between institutions and individual shareholders. Section 3 constructs portfolios based on formation-period trade imbalance to analyze its impact on the profitability of momentum strategies. Section 4 concludes the article.

1. Data Sample and Construction of Variables

The sample in the current study includes all ordinary common stocks listed on the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX) in the period January 1983 through December 2002. REITS, stocks of companies incorporated outside the U.S., and closed-end funds are eliminated from the sample. All return data are from the Center for Research in Security Prices (CRSP) files. Stocks are classified by industry according to the two-digit Standard Industrial Classification (SIC) groupings used in Moskowitz and Grinblatt (1999).[5] 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. Unsigned share volume data are from CRSP, and the volume measure used is share turnover, computed as the daily number of shares traded divided by the number of shares outstanding for a given stock.

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/Nasdaq in 1983–1992, 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.[6]

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

[5] Moskowitz and Grinblatt (1999) construct 20 industry-based groupings. However, SIC code 40 (railroads) had relatively few stocks and was merged with codes 41–47 (other transportation), resulting in 19 industry portfolios in the current study.

[6] The Appendix describes the trade and quote filters.

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 then classified as either buys or sells, and as small, medium, or large trades (as made precise below). The directional trade volume is measured each day for each size group, and the subsequent analyses are based on this daily data.

Individual stock trade imbalances are computed as

$$\widehat{\mathrm{IMBAL}}_{git} = \begin{cases} \dfrac{\mathrm{BUYVOL}_{git} - \mathrm{SELLVOL}_{git}}{(\mathrm{BUYVOL}_{git} + \mathrm{SELLVOL}_{git})/2}, \\ 0, \\ \max\left(\mathrm{BUYVOL}_{git}, \mathrm{SELLVOL}_{git}\right) > 0, \\ \text{otherwise} \end{cases} \tag{1}$$

where BUYVOL_{git} ($\mathrm{SELLVOL}_{git}$) is the buy-initiated (sell-initiated) volume for stock i on day t based on the trades in size group $g \in \{s, m, l\}$ for small, medium, and large trades. Note that the trade imbalance is measured relative to the average of the buy and sell volume.

The underlying idea of the approach taken in this article is that trade imbalances could be related to mispricing. If correct, then the expected trade imbalance of a given stock could depend on any stock characteristic, which might be related to mispricing. That is, the expected trade imbalance could vary across stocks, and so to isolate the effect of momentum on imbalances, one needs to control for the effect of other characteristics. To this end, $\widehat{\mathrm{IMBAL}}$ is regressed against several characteristics, and the error term is used as the measure of abnormal imbalance. As regressors, I also include characteristics that have been linked to trading activity, hence which might affect trade imbalances as well. Specifically, the following cross-sectional regression is run each day t in the sample period (t subscripts are suppressed for ease of notation):

$$\begin{aligned} \widehat{\mathrm{IMBAL}}_{gi} = \delta_0 &+ \delta_1 \mathrm{SIZE}_i + \delta_2 \mathrm{BM}_i + \delta_3 \mathrm{AMEX}_i + \delta_4 \mathrm{SP500}_i \\ &+ \delta_5 \hat{\sigma}_i + \delta_6 \mathrm{SPREAD}_i + \delta_7 \hat{\gamma}_i(1) + \delta_8 \mathrm{DIVYLD}_i \\ &+ \sum_{j=1}^{18} \gamma_j \mathrm{SIC}_{ij} + \mathrm{IMBAL}_{gi}, \end{aligned} \tag{2}$$

where SIZE_i is the logarithm of the market capitalization of stock i at the end of year $s-1$; BM_i is the logarithm of the book-to-market value of equity for stock i in year $s-1$; AMEX_i is an indicator variable equal to 1 if stock i is listed on the American Stock Exchange; $\mathrm{SP500}_i$ is an indicator variable equal to 1 if stock i is a member of the Standard and Poor's 500 index; $\hat{\sigma}_i$ is the logarithm of the standard deviation of weekly returns for stock i over year $s-1$; SPREAD_i is the logarithm of the average opening percentage quoted bid–ask spread for stock i during year $s - 1$;[7] $\hat{\gamma}_i\,(1)$ is the first-order autocovariance of daily returns for stock i during year $s - 1$; DIVYLD_i is the average of the monthly dividend yields for stock i during year $s - 1$; and SIC_{ij} is an indicator variable equal to 1 if stock i belongs to industry j. The error term IMBAL_{gi} is then used as the measure of abnormal trade imbalance for trade size group g in stock i on day t.

In regression (2), SIZE, BM, and SIC are included as they are standard controls for returns and could be related to mispricing. Of course, these variables might also be related to genuine factors driving expected returns. In that case, if demand by different investors is driven by their different risk preferences, then expected trade imbalances could depend on these factors, which then need to be controlled for. The standard deviation of returns, $\hat{\sigma}$, is included to capture effects from total risk. In addition, investor demand could be related to firm visibility and investor recognition (Merton, 1987). Larger firms, firms in the S&P 500, and NYSE-listed firms are more likely to be visible to investors. The S&P 500 indicator variable is also included to capture any effects from index-related arbitrage and from trading by mutual funds tracking the index.

Amihud and Mendelson (1986) suggest that trading costs lead to an investor clientele effect as longer term investors hold more illiquid stocks. Hence, investor demand might also be related to the illiquidity of a stock, and the quoted spread and the first-order autocovariance of returns, $\hat{\gamma}(1)$, are included as illiquidity measures. Roll (1984) shows that under certain conditions, the effective bid–ask spread can be computed as $\sqrt{-\hat{\gamma}(1)}/2$. Following Lo and Wang (2000), I simply use $\hat{\gamma}(1)$ to avoid complex numbers for the spread when $\hat{\gamma}(1) > 0$.

Lastly, the dividend yield is included as a regressor, because differences in dividends also could result in an investor clientele effect, which, if different clienteles have different horizons, could affect trading activity. Also, dividend payments can generate trading as some investors attempt to capture differences between dividends and returns around the ex-dividend day [see Lo and Wang (2000) and references therein].[8]

Portfolio trade imbalances IMBAL_{gpt} are then computed each day t for trade-size group g as the average of the abnormal imbalances of the n stocks in portfolio p:

$$\mathrm{IMBAL}_{gpt} = \frac{1}{n}\sum_{i \in p} \mathrm{IMBAL}_{gpt}. \tag{3}$$

[7] Since the spread data are extracted from ISSM/TAQ, hence available starting in 1983, SPREAD is only included in the regressions for 1984–2002.

[8] As an alternative to Equation (2), I used a benchmark-adjustment based on size, BM, and industry portfolios to extract abnormal trade imbalances. This captures nonlinear effects of size and BM on imbalances. Results (unreported) were qualitatively identical to those reported below.

All trades were classified by size using a variation of the Lee (1992) firm-specific dollar-based trade-size proxy. Lee (1992) notes that while a dollar-based size proxy is conceptually superior to one based on the number of shares traded, the dollar-based proxy is sensitive to small price changes.[9] Therefore, he suggests obtaining a closing price during the sample period, comparing that price to, say, \$10,000, and determining the largest number of round lot shares that is less than or equal to \$10,000. Trades at this number of shares or less are deemed small trades. Furthermore, using the TORQ 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 providing an intermediate buffer zone between small and large trades and by conditioning the cut-off point on firm size. Liquidity is generally lower among smaller firms; hence institutions trade in smaller trade sizes in those firms.

Each month end, firm size and CRSP closing price are obtained for each stock. Firm size quintiles are formed, and firm-specific cut-off points are determined by comparing the closing price to a firm-size-quintile-specific dollar value. The cut-off points were calibrated based on the data in Lee and Radhakrishna (2000, Tables 5–8) to maximize the number of individual (institutional) trades in the small-trade (large-trade) bracket and to minimize the institutional (individual) trades in the small-trade bracket as a fraction of all small (large) trades. The cut-off points were also based on minimizing the number of firms ineligible for small trades due to high prices and on making this number orthogonal with firm size. Specifically, the cut-off points were obtained as follows. Each month s, stocks are sorted into quintiles based on firm size. Within each size quintile j, the 99th stock price percentile ($P99_{js}$) is found, and $P99_j$ is computed as the average of $P99_{js}$ across all months in the sample. Small-trade cut-off points are then set as $100 \times P99_j$ rounded up to the nearest \$100, and large-trade cut-off points are $200 \times P99_j$. Therefore, roughly one percent of the firms in the sample will not have any small trades. The trade-size classification for individual stocks then follows the Lee (1992) algorithm by using the month $s - 1$ closing price for determining the number of shares cut-off points for all trades in month s.[10]

[9] For instance, if the current bid and ask prices were \$25.00 and \$25.125, respectively, a \$10,000 cut-off point would classify trades at the bid in sizes of 100–400 shares as small, while, at the ask, only trades in sizes 100–300 shares would be classified as small.

[10] As an alternative measure, trades were size-classified based on the number of shares traded. Trades of less than 1000 shares were classified as small, and trades of 2000 or more shares were classified as large. This produced very similar (unreported) results to those based on the dollar-value of trades.

The procedure results in the following cut-off points:[11]

Firm-size quintile	Small	2	3	4	Large
Small trade cut-off, in $	3400	4800	7300	10,300	16,400
Large trade cut-off, in $	6800	9600	14,600	20,600	32,800

The intermediate size group is created as a buffer zone to increase the power in detecting differences in trading behavior between small and large traders. Therefore, the analysis below focuses on small and large trades.

2. Trading Pressures in Momentum Portfolios

The behavioral finance literature suggests that individuals use heuristics or suffer from cognitive biases, leading them to hold particular risk-return models and thus affecting their demand for risky assets and the prices of those assets. Shleifer (2000, p. 183), for example, argues that

> different investors form different models of the future and trade with each other. Trading volume is substantial, especially when different models generate different demands. But when models lead to similar predictions, investors try to *buy* the same securities at the same time, *thereby driving up prices* without any fundamental news. (italics added)

In other words, the link between cognitive biases and asset prices is the *actions* of investors. Specifically, the biases determine investors' buying and selling behavior, which, in turn, influences asset prices. Therefore, we can analyze aggregate trading behavior in conjunction with an asset pricing anomaly, such as momentum, to examine whether trading pressures are consistent with a given hypothesis.

Table 1 gives a summary of the imbalances suggested by different models of investor reaction to momentum. First, it is instructive to examine expected trade imbalances under a simple rational model, such as Conrad and Kaul (1998), who suggest that momentum could be due entirely to cross-sectional variation in unconditional expected returns, not time-series predictability. By construction, good news arrives for the winners during the portfolio formation period. News arrives either as private information which is impounded into prices via trading by informed investors or as public information, in which case prices would adjust before any trading takes place. In the former case, we expect a relative buying pressure among winners, while in the latter case, we would not expect any particular directional trading patterns. Generally, with

[11] It is worth noting that the distribution of stock prices is relatively invariant across years. For instance, using only the first half of the sample would yield the following small-trade cut-off points: 3400, 4200, 7000, 8400, and 17,200.

Table 1
Hypotheses of momentum and their trade implications

Hypothesis		Formation period	Holding period	
			Initially	Subsequently
Differences in expected returns	Winners	$\text{IMBAL}^{(b)} > 0$	$\text{IMBAL} = 0$	$\text{IMBAL} = 0$
	Losers	$\text{IMBAL}^{(s)} < 0$	$\text{IMBAL} = 0$	$\text{IMBAL} = 0$
Underreaction/delayed reaction	Winners	$\text{IMBAL} < \text{IMBAL}^{(b)}$	$\text{IMBAL} < 0$	$\text{IMBAL} > 0$
	Losers	$\text{IMBAL} > \text{IMBAL}^{(s)}$	$\text{IMBAL} > 0$	$\text{IMBAL} < 0$
Momentum trading	Winners	$\text{IMBAL} > 0$	$\text{IMBAL} > 0$	$\text{IMBAL} = 0$
	Losers	$\text{IMBAL} < 0$	$\text{IMBAL} < 0$	$\text{IMBAL} = 0$

The trade imbalances suggested by different hypotheses of momentum and by momentum trading. $\text{IMBAL} > 0$ indicates a buying pressure and $\text{IMBAL} < 0$ indicates a selling pressure. $\text{IMBAL}^{(b)}$ is the benchmark formation-period buying pressure for winners caused by possible informed traders, while $\text{IMBAL}^{(s)}$ is the benchmark formation-period selling pressure for losers.

both private and public information, a buying pressure, say $\text{IMBAL}^{(b)} > 0$, would therefore be expected during the formation period. Among losers, we would, by the same argument, expect a formation-period selling pressure, $\text{IMBAL}^{(s)} < 0$. After the formation period, the simple unconditional expected returns model does not predict any buy/sell imbalances for winners or losers.

If investor demand prevents prices from adjusting fully to public news, then we expect a buying pressure among losers and selling pressure among winners. During the formation period, however, privately informed traders would buy winners and sell losers.[12] Therefore, the net formation-period trade imbalance with both initial underreaction and informed trading would be, among winners, either a selling pressure or a weaker buying pressure than under the rational model, i.e. $\text{IMBAL} < \text{IMBAL}^{(b)}$. Likewise, a buying pressure or a weaker selling pressure is predicted among losers, namely $\text{IMBAL} > \text{IMBAL}^{(s)}$. However, since $\text{IMBAL}^{(b)}$ and $\text{IMBAL}^{(s)}$ depend on the relative importance of private and public information, which are unobservable, evidence of underreaction would be inconclusive unless there is a selling pressure among winners or a buying pressure among losers.

After the formation period, news no longer arrives by construction; hence the effect of any informed trading disappears. Initial underreaction therefore predicts a selling pressure among winners and a buying pressure among losers. By contrast, delayed reaction implies an eventual buying (selling) pressure among winners (losers) as investors are reacting to the earlier positive (negative) news. With both initial underreaction and delayed reaction, a gradual shift from initial selling pressure to delayed buying pressure would appear among winners, and an initial buying pressure followed by a selling pressure would appear among losers.

[12] If informed traders also underreact, they would buy (sell) less in response to a high (low) private signal than under the rational benchmark.

These event-time shifts in the trade imbalances are key predictions of the behavioral models. Since momentum is profitable over horizons of up to one year, any such shifts would be expected to occur over that period. By comparison, if differences in realized returns are due to differences in expected returns, as in Conrad and Kaul (1998), then buy/sell imbalances might not be zero if different investors prefer stocks with different risk characteristics [and the imbalance adjustment in Equation (2) does not properly capture such differences]. It is less clear, however, how such a model could produce, say, an initial buying pressure among losers followed by a delayed selling pressure.

Many articles have analyzed the trading behavior of institutions, based on quarterly changes in institutional holdings, and generally found that institutions engage in momentum trading.[13] Consequently, we might expect large-trade imbalances to reflect momentum trading, with an initial buying pressure among winners and an initial selling pressure among losers.

2.1 Event-time trade imbalances

The above predictions are evaluated using event-time trade imbalances relative to the monthly portfolio formation date. Momentum portfolios are formed on the first trading day of each month in the sample by sorting all stocks into deciles according to prior six-month returns. Losers are in decile one and winners are in decile 10. Figure 1 shows the portfolio trade imbalances in event-time for small and large trades in the top and bottom panel, respectively. On the horizontal axis, data 0 represents the monthly portfolio formation date. Daily imbalances are shown from date –120 to date 500. That is, from 120 trading days before the formation date, corresponding approximately to the beginning of the six-month formation period, to about 2 years after the portfolio formation. The imbalances are computed for losers and winners by first computing the event-time daily portfolio imbalance for each formation date and then averaging the daily imbalances across formation dates. To avoid clutter, the standard errors of the daily event-time mean imbalances are not plotted. Instead, the mean and maximum of the 621 standard errors are shown in a table inserted in the figures.

Several key findings emerge. For small trades, a buying pressure among losers exists during most of the formation period. The standard errors, though, imply a two-standard-error bound of around 1.1%, so the individual daily imbalance points are not consistently significant. However, the buying pressure becomes very strong and significant on the formation

[13] Among others, see Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999), Chen, Jegadeesh, and Wermers (2000), Gompers and Metrick (2001), and Badrinath and Wahal (2002), and Burch and Swaminathan (2001). Also, using Finnish transaction-level data over a two-year period which identify all traders, Grinblatt and Keloharju (2001) find that institutions tend to be momentum traders.

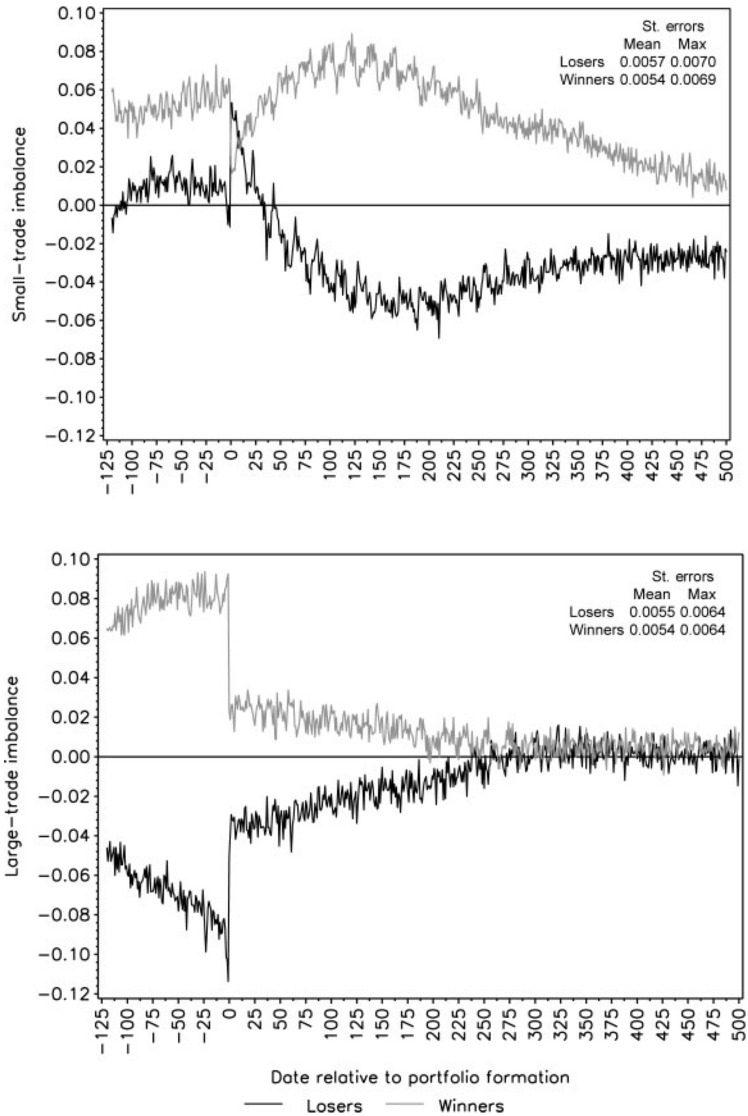

Figure 1
Small- and large-trade imbalances
Using NYSE/AMEX common stocks, momentum deciles are formed each month in 1983–2002 based on prior six-month returns. Event-time small-trade (top panel) and large-trade (bottom panel) imbalances are shown for losers and winners. Daily abnormal imbalances are computed for each stock. For each formation date, daily event-time portfolio trade imbalances are computed by averaging the imbalances of the stocks in the portfolio. The figures then contain the means for each event-time day across formation dates, and the inserted tables report statistics on the standard errors of these means. "Mean" and "max" are the average and maximum standard error across event-time days. Date 0 is the monthly portfolio formation date, –125 is 125 trading days before the formation date, corresponding to approximately the start of the formation period, and 500 is about 2 years hence.

date and remains positive over the following 35 days.[14] Then, a selling pressure slowly sets in and reaches a maximum of around 200 days after the formation date. Thus, the evidence is consistent with small investors initially underreacting, and while they do eventually sell losers, they apparently react extremely slowly to the negative formation-period information. Among winners, there is a formation-period buying pressure which largely disappears on the formation date, and a buying pressure again sets in slowly over the following 100 trading days. Thus, while evidence of initial small-investor underreaction exists only among losers, both winner and loser stocks exhibit a delayed imbalance, consistent with delayed small-investor reaction. The stronger result among losers is consistent with the findings in Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004) that the bulk of momentum profits come from shorting losers.

The pattern of large-trade imbalances in the bottom panel of Figure 1 is strikingly different. A large-trade buying pressure of 6–9% exists among winners during the formation period. Then, a significant drop to around 2% occurs on the formation date, and the buying pressure gradually disappears over the following year. A largely symmetric selling pressure occurs among losers: During the formation period, a strong selling pressure exists, which diminishes on the formation date to around 3% and then also gradually disappears over the following year. Thus, large traders sell losers and buy winners during the formation period, consistent with informed trading, and appear to be (early-stage) momentum traders, consistent with the evidence based on quarterly changes in institutional holdings.

2.2 The effect of trading volume

Lee and Swaminathan (2000) show that high-volume losers underperform low-volume losers by around 1% per month, while little difference exists in the returns of low- and high-volume winners. In other words, momentum is stronger among high-volume stocks. They also find that "high volume stocks are generally *glamour* stocks and low volume stocks are generally *value* or *neglected* stocks" (p. 2049), based on analysts following, forecasted earnings, book-to-market ratios, and return-on-equity. They suggest that volume provides information on the extent to which investor sentiment favors a stock at a particular point in time. Since the small-trade imbalance is a plausible measure of small-investor sentiment, we would, if the sentiment hypotheses are correct, expect a positive correlation between volume (or turnover) and small-trade imbalances. Moreover, if momentum is partly driven by trade imbalances, we would expect a stronger delayed selling

[14] The noncontinuity at date zero is particularly strong around the turn of the year. Using only January formation dates, a 28.2% change in trade imbalances appears between days –1 and 0, while the change is 4.6% when using February through December formation dates. Still, the buying pressure following the formation date remains positive and significant outside the month of January. Section 2.3 analyzes the seasonality of the trade imbalances.

pressure for high-turnover losers than for low-turnover losers and/or stronger formation-period buying pressure for high-turnover losers. To study the possible interaction between volume and trade imbalances, I sort losers and winners into terciles based on past six-month share turnover.

The results show that a strong correlation indeed exists between formation-period volume and small-trade imbalances among losers, but not among winners. The top panel of Figure 2 shows a very strong formation-period *buying* pressure among high-volume losers of 10–14%. This buying pressure turns into a selling pressure over the year following the formation date. By contrast, Figure 3 shows a strong formation-period small-trade *selling* pressure among low-volume losers. After the formation date, this selling pressure becomes somewhat weaker. The results therefore indicate initial underreaction among high-volume, but not low-volume, losers. This is consistent with the evidence that loser underperformance is especially prevalent among high-volume losers. Among winners, a small-trade buying pressure exists during the formation period for both high-volume and low-volume stocks, consistent with the evidence of little difference in future returns between high- and low-volume winners.

The large-trade imbalances across volume portfolios are also interesting. The bottom panel of Figure 2 shows evidence of momentum trading in high-volume stocks similar to Figure 1, while Figure 3 shows no evidence of loser selling pressure or winner buying pressure after the formation date among low-volume stocks. Indeed, to the extent that the large-trade imbalances reflect active institutional momentum trading, we would expect these trade imbalances to be weaker among low-turnover stocks, since the evidence of momentum is relatively weak among low-volume stocks.

2.3 Seasonality of trade imbalances

A potential concern about the preceding results indicating delayed reaction among small traders could be that this simply reflects year-end tax-motivated trading. Likewise, the initial small-trade buying pressure among losers might be driven by tax-related buying pressures in January. While tax-loss selling would not appear to be able to explain why the trading pressures do not peak until almost a year after the formation date, it is nevertheless instructive to examine the seasonal component of the trade imbalances.

Extensive evidence exists that investors engage in tax-loss selling,[15] and Grinblatt and Moskowitz (2004) show evidence that tax-loss selling affects the seasonality of momentum profitability. If investors engage in tax-loss selling, we would expect a selling pressure among losers toward the end of the year. Further, investors might avoid selling winners toward

[15] See, e.g., Lakonishok and Smidt (1986), Badrinath and Lewellen (1991), Dyl and Maberly (1992), Sias and Starks (1997), Odean (1998), and Grinblatt and Keloharju (2004).

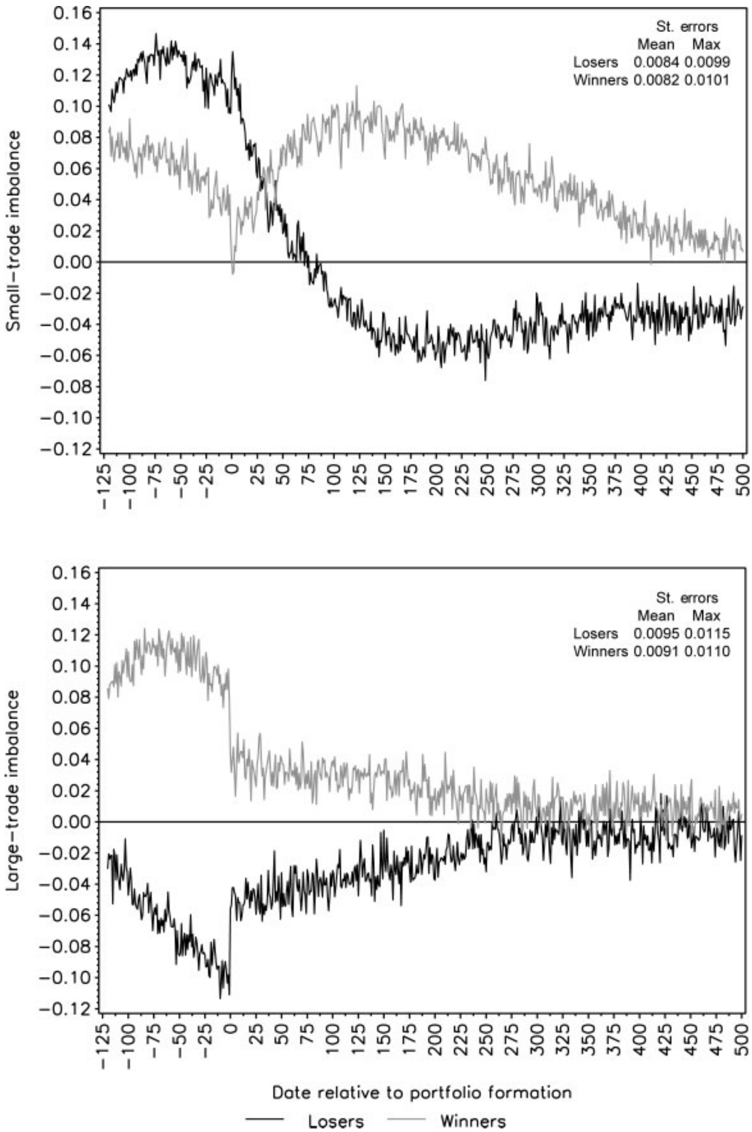

Figure 2
Small- and large-trade imbalances among high-turnover stocks
Using NYSE/AMEX common stocks, momentum deciles are formed each month in 1983–2002 based on prior six-month returns. Stocks are then sorted into terciles based on past six-month turnover. Event-time small-trade (top panel) and large-trade (bottom panel) imbalances are shown for high-turnover losers and winners. Daily abnormal imbalances are computed for each stock. For each formation date, daily event-time portfolio trade imbalances are computed by averaging the imbalances of the stocks in the portfolio. The figures then contain the means for each event-time day across formation dates, and the inserted tables report statistics on the standard errors of these means. "Mean" and "max" are the average and maximum standard error across event-time days. Date 0 is the monthly portfolio formation date, –125 is 125 trading days before the formation date, corresponding to approximately the start of the formation period, and 500 is about 2 years hence.

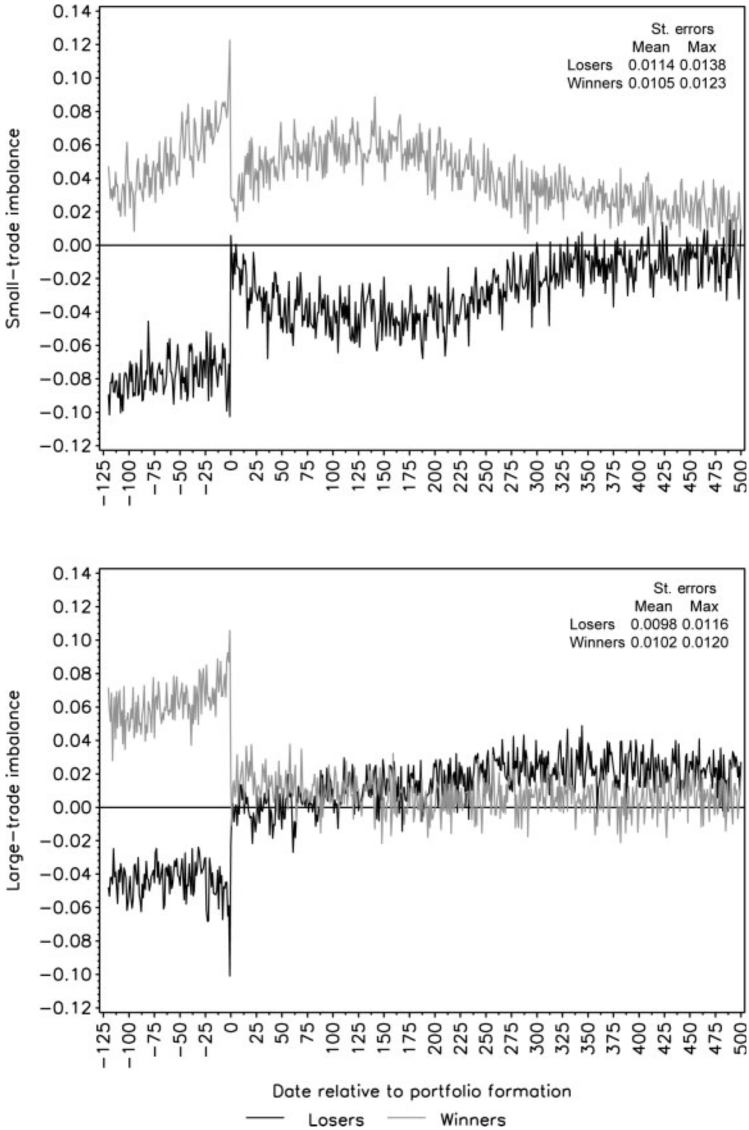

Figure 3
Small- and large-trade imbalances among low-turnover stocks
Using NYSE/AMEX common stocks, momentum deciles are formed each month in 1983–2002 based on prior six-month returns. Stocks are then sorted into terciles based on past six-month turnover. Event-time small-trade (top panel) and large-trade (bottom panel) imbalances are shown for low-turnover losers and winners. Daily abnormal imbalances are computed for each stock. For each formation date, daily event-time portfolio trade imbalances are computed by averaging the imbalances of the stocks in the portfolio. The figures then contain the means for each event-time day across formation dates, and the inserted tables report statistics on the standard errors of these means. "Mean" and "max" are the average and maximum standard error across event-time days. Date 0 is the monthly portfolio formation date, –125 is 125 trading days before the formation date, corresponding to approximately the start of the formation period, and 500 is about 2 years hence.

the end of the year, to delay recognizing taxable gains, thus creating a buying pressure among winners at year end. Since the potential benefits from tax-related trading primarily accrue to individuals, we would expect stronger seasonality among small trades under the hypothesis of tax-related trading. Alternatively, mutual fund managers might engage in window dressing [see Lakonishok et al. (1991)], which could generate a large-trade selling pressure among losers and a large-trade buying pressure among winners at the end of the year. However, the current focus is not to distinguish between different explanations of seasonality in trading pressures. Rather, it is to ensure that the trading pressures uncovered above are not driven purely by trading behavior related to the calendar.

To analyze trading pressures across the year, two holding periods are assumed. First, to ensure that the initial small-trade buying pressure among losers is not driven solely by buying in January, I analyze the seasonality of a momentum strategy which is invested in during the month immediately following the formation date. Second, to ensure that the delayed small-trade buying (selling) pressure among winners (losers) is not due to year-end trading, I analyze the seasonality of a strategy invested in months 10–12 after the formation date.

The daily abnormal trade imbalance is computed using Equation (3) for winners and losers during the holding period for each formation date. Next, a time series of daily imbalances is constructed by averaging across prior formation dates, with holding periods that span a given date. The trade imbalance for each trading day of the year is then the average for the given day of the year across the 1983–2002 period.[16] Figures 4 and 5 show the daily small-trade imbalances (top panels) and large-trade imbalances (bottom panels) among winners and losers for the 1-month and 10- to 12-month strategies, respectively. In addition, to conduct statistical tests of imbalances across the year, the following regression was estimated:

$$\mathrm{IMBAL}_{pt} = \sum_{s=1}^{12} I_{(s=d)} \delta_{ps} + \varepsilon_{pt},$$

where IMBAL_{pt} is the trade imbalance for portfolio p on day t over the period 1983–2002. $I_{(s\,=\,d)}$ is an indicator variable equal to 1 if $s = d$, where $d = 1,...,12$, corresponding to January through December, and 0 otherwise. The regression standard errors are estimated using the Newey–West procedure, with 15 lags to correct for autocorrelation and heteroskedasticity. The results are reported in Table 2.

The top panel of Figure 4 shows that the small-trade imbalances for both winners and losers exhibit a market turn-of-the-year pattern in the month after the formation date. Among losers, a strong buying appears in the first

[16] Most years have 252 trading days, and a few have 253 or 254 days. To focus on the turn of the year, I take a trading year to be the first 150 days followed by the last 102 days.

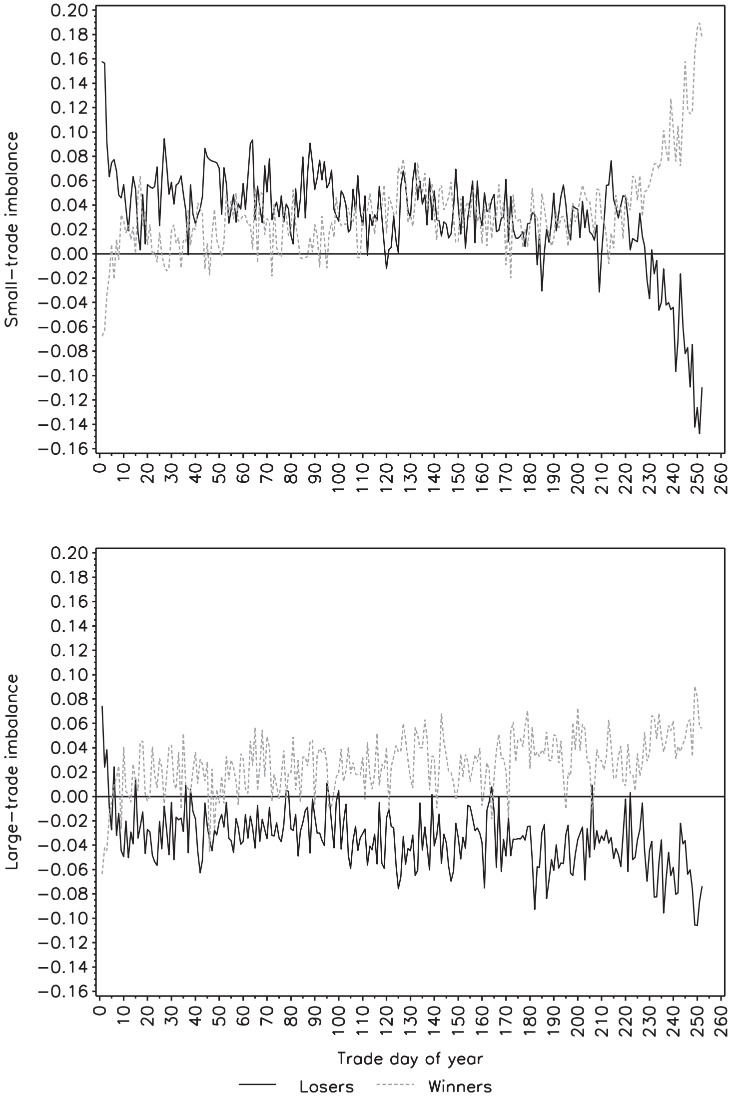

Figure 4
Small- and large-trade imbalances by day-of-year: one-month holding period
Using NYSE/AMEX common stocks, momentum deciles are formed each month in 1983–2002 based on prior six months returns. The holding period is one month, beginning on the formation date. Holding period small-trade (top panel) and large-trade (bottom panel) imbalances by day-of-the-year are shown for losers and winners. Daily abnormal imbalances are computed for each stock. For each formation date, daily portfolio trade imbalances during the holding period are computed by averaging the imbalances of the stocks in the portfolio. This creates a time series of daily portfolio imbalances. For each trading day of the year, the trade imbalance is then obtained by averaging across the given day in each of the years in the sample period. Day 1 (252) is the first (last) trading day of the year.

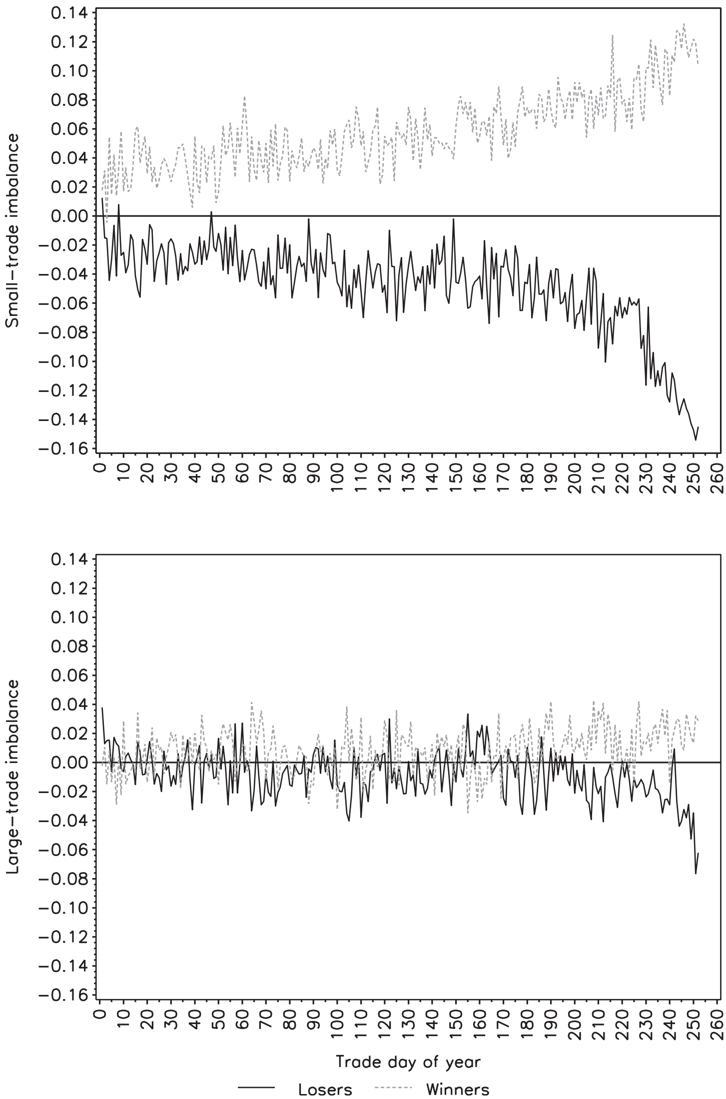

Figure 5

Small- and large-trade imbalances by day-of-year: 10- to 12-month holding period

Using NYSE/AMEX common stocks, momentum deciles are formed each month in 1983–2002 based on prior six months returns. The holding period is three months, beginning nine months after the formation date. Holding period small-trade (top panel) and large-trade (bottom panel) imbalances by day-of-the-year are shown for losers and winners. Daily abnormal imbalances are computed for each stock. For each formation date, daily portfolio trade imbalances during the holding period are computed by averaging the imbalances of the stocks in the portfolio. A time series of portfolio imbalances is then constructed by averaging, for each trading day in the sample, the imbalances over the prior three holding periods that span the given date. For each trading day of the year, the trade imbalance is then obtained by averaging across the given day in each of the years in the sample period. Day 1 (252) is the first (last) trading day of the year.

Table 2
Seasonality in trade imbalances

	One-month strategy				10- to 12-month strategy			
	Small trades		Large trades		Small trades		Large trades	
Parameter	Losers	Winners	Losers	Winners	Losers	Winners	Losers	Winners
δ_1	0.059 (7.57)	0.007 (0.05)	–0.015 (–2.85)	0.002 (0.94)	–0.024 (–5.22)	0.034 (6.68)	0.006 (1.39)	–0.001 (–0.35)
δ_2	0.050 (5.93)	0.008 (1.02)	–0.027 (–4.35)	0.020 (3.92)	–0.029 (–5.88)	0.033 (6.55)	–0.007 (–1.57)	0.008 (1.54)
δ_3	0.057 (7.35)	0.022 (2.79)	–0.031 (–6.04)	0.012 (2.13)	–0.024 (–4.55)	0.043 (11.4)	–0.002 (–0.35)	0.007 (2.04)
δ_4	0.043 (5.02)	0.023 (2.41)	–0.024 (–5.18)	0.023 (4.13)	–0.036 (–6.92)	0.041 (7.85)	–0.014 (–3.03)	0.009 (2.43)
δ_5	0.055 (6.31)	0.014 (1.69)	–0.020 (–4.59)	0.023 (4.05)	–0.033 (–6.83)	0.043 (10.9)	–0.006 (–1.41)	0.002 (0.67)
δ_6	0.025 (3.02)	0.034 (3.99)	–0.041 (–6.79)	0.025 (4.60)	–0.044 (–10.3)	0.050 (11.6)	–0.009 (–2.41)	0.003 (0.83)
δ_7	0.041 (5.04)	0.047 (5.02)	–0.040 (–7.84)	0.035 (6.30)	–0.040 (–6.94)	0.053 (10.8)	–0.008 (–1.91)	0.007 (1.48)
δ_8	0.033 (3.60)	0.034 (3.95)	–0.030 (–4.86)	0.021 (3.07)	–0.043 (–9.53)	0.062 (9.28)	0.003 (0.67)	–0.001 (–0.37)
δ_9	0.016 (1.58)	0.024 (2.33)	–0.046 (–5.14)	0.036 (6.17)	–0.047 (–8.60)	0.066 (9.83)	–0.014 (–2.48)	0.010 (2.25)
δ_{10}	0.021 (2.38)	0.033 (3.10)	–0.042 (–6.16)	0.031 (5.07)	–0.056 (–13.5)	0.077 (11.7)	–0.011 (–2.00)	0.015 (4.33)
δ_{11}	0.025 (2.32)	0.035 (3.61)	–0.037 (–5.90)	0.028 (4.65)	–0.071 (–12.2)	0.083 (12.1)	–0.016 (–3.47)	0.013 (2.92)
δ_{12}	–0.065 (–7.10)	0.113 (10.1)	–0.068 (–9.33)	0.051 (8.07)	–0.121 (–22.5)	0.110 (15.4)	–0.031 (–6.78)	0.021 (4.88)
Overall significance	277.8 [0.00]	180.6 [0.00]	384.4 [0.00]	247.6 [0.00]	1210.9 [0.00]	1189.9 [0.00]	89.15 [0.00]	70.98 [0.00]

Using NYSE/AMEX stocks, momentum deciles are formed each month in 1983–2002 based on prior six-month returns. The holding period is either one month beginning on the formation date (*one-month strategy*) or three months beginning nine months after the formation date (*10- to 12-month strategy*). Daily abnormal imbalances are computed for each stock. For each formation date, daily portfolio trade imbalances during the holding period are computed by averaging the imbalances of the stocks in the portfolio. A time series of portfolio imbalances is then constructed by averaging, for each trading day, the imbalances over the prior holding periods that span the given date. The following model was estimated:

$$\mathrm{IMBAL}_{pt} = \sum_{i=1}^{12} I_{(i=d)}\delta_{pi} + \varepsilon_{pt},$$

where IMBAL_{pl} is the imbalance for momentum portfolio p on day t. $I_{(i\,=\,d)}$ is an indicator variable equal to 1 if i is equal to d, where $d = 1,...,12$, corresponding to January–December, and 0 otherwise. Newey–West corrected t-values are in parentheses for the individual parameter estimates and p-values are in square brackets for the test for joint significance of the δ parameters (asymptotically distributed as a $\chi^2_{(12)}$ under the null).

days of January pressure, and an increasing selling pressure occurs throughout December. An almost opposite pattern exists among winners, with a brief selling pressure in the beginning of January and a mounting buying pressure throughout December. However, the initial small-trade buying pressure among losers, shown in Figure 1, is not confined to the month of January. The loser small-trade imbalances are generally positive in January through November, and Table 2 shows that they are also significant in those months (t-statistics 2.32 to 7.98), except for September. Therefore, while the small-trade imbalances contain an important seasonal component, the evidence of initial underreaction among losers is not simply driven by January buying pressures.

The turn-of-the-year pattern is also evident in the small-trade imbalances for the 10- to 12-month holding period shown in the top panel of Figure 5. However, the delayed selling pressure for losers and delayed buying pressure for winners are apparent and statistically significant (as shown in Table 2) throughout the year. The large-trade imbalances in the bottom panels of Figures 4 and 5 also show evidence of seasonality. However, while statistically significant, it is less pronounced than the seasonality of the small-trade imbalances.

2.4 A discussion of the results

The Lee and Ready (1991) algorithm employed in this article has been used extensively in the market microstructure literature. While it generally performs well, it could introduce biases in the classification. For instance, Finucane (2000) argues that signed volume is more likely to be underestimated for larger trades. While unlikely, given the nature of the data, one cannot completely rule out that some of the systematic differences in trade imbalances across size groups and momentum portfolios could partly be caused by biases introduced by the algorithm. It is not possible to reject such claims without access to order level data. However, the central results above, namely the differential patterns over time, such as the delayed reaction pattern among small, but not large, traders, cannot be explained by simple biases in the Lee and Ready (1991) algorithm.

As noted earlier, several recent articles have inferred the trading behavior of institutions using holdings data, which are available at quarterly frequency. The results on large-trade imbalances are consistent with institutional investors engaging in momentum trading. Moreover, the finding that momentum trading among large traders primarily occurs in high-volume stocks is consistent with the findings in Burch and Swaminathan (2001), who show that institutional momentum trading is concentrated in high-volume stocks. However, some care is needed in interpreting the results as reflecting the trading behavior of institutions *as a group*. That is, the measure of imbalance among large trades is likely to be driven by the behavior of institutional traders, which, however, includes trading between institutions that demand liquidity and those supplying liquidity. Likewise, the small-trade imbalances could partly reflect trading between individuals demanding liquidity and those supplying it. Therefore, to analyze the extent to which the small- and large-trade imbalances reflect trading between individuals and institutions, I compare the imbalances with changes in institutional holding based on the 13f data.

To compare the trade imbalance measures and institutional trading, six-month net signed institutional turnover for each stock, Δhold, was computed as the number of shares bought minus the number of shares sold by 13f institutions over the past two quarters, divided by the number of shares outstanding at the end of the second quarter. Momentum deciles are then formed every quarter based on past six-month returns, and analysis is done within each momentum portfolio. The top panel of Table 3 shows that institutions sold on average 1.8% of the shares outstanding in losers during the formation period and bought on average 3.2% of the shares outstanding among winners. This is consistent with the directions of the large-trade imbalances in Figure 1. Also, cross-sectional correlations of the small- and large-trade imbalances with Δhold during the formation period were computed within each momentum portfolio, and the panel reports the average correlations across formation dates. The correlations between the small-trade imbalance, $IMBAL_s$, and Δhold

Table 3
Trade imbalances and changes in institutional holdings during the formation period

			Corr(Δhold, ·)	
		Δhold	$IMBAL_s$	$IMBAL_l$
Losers		–0.018	–0.243	0.053
Winners		0.032	–0.050	0.167
			Δhold portfolio	
		1	3	1–3
Losers	Δhold	–0.088	0.047	–0.135
	$IMBAL_s$	0.102	–0.046	0.148
	$IMBAL_l$	–0.089	–0.068	–0.021
Winners	Δhold	–0.041	0.117	–0.158
	$IMBAL_s$	0.064	0.027	0.037
	$IMBAL_l$	0.051	0.112	–0.061

Momentum deciles are formed at the beginning of each quarter in 1983–2002 based on past six-month returns. Losers are in decile one and winners are in decile 10. Formation-period net signed institutional turnover for each stock, Δhold, is computed as the number of shares bought minus the number of shares sold by 13f institutions over the past two quarters, divided by the number of shares outstanding. The table reports the average Δhold for each portfolio across formation dates. Formation-period trade imbalances are computed for each stock as the average of the daily abnormal trade imbalances. $IMBAL_s$ and $IMBAL_l$ are small- and large-trade imbalances, respectively. Corr(Δhold, ·) is the average across formation periods of the Spearman cross-sectional correlations between Δhold and the trade imbalances within momentum portfolios. In the bottom panel, stocks are sorted within momentum portfolios into terciles based on Δhold. The formation-period imbalances are averaged across stocks each formation date, and the table reports the average imbalance per portfolio across formation dates.

are negative, while the correlations between IMBAL_l and Δhold are positive. This is consistent with small-trade imbalances reflecting individual trading behavior and large-trade imbalances reflecting institutional trading. However, the correlations are relatively low.

To provide another perspective on the relationship between the imbalance measures and changes in institutional holdings, losers and winners were sorted into terciles based on Δhold. The bottom panel of Table 3 reports the average formation-period small- and large-trade imbalances for those portfolios, along with the average Δhold. Among losers with most institutional selling, institutions sold on average 8.8% of the shares outstanding. Since institutions are selling, we expect buying by individuals in those stocks, and indeed small traders show a strong buying pressure of 10.2%. Vice versa, losers with institutional buying show a selling pressure among small traders of 4.6%. The large-trade imbalance, by contrast, shows a positive correlation with Δhold. However, a large-trade selling pressure occurs among losers even in the stocks with high Δhold, and, a large-trade buying pressure occurs among winners even in the stocks with low Δhold. In summary, both the small- and large-trade imbalances hold information about the changes in institutional holdings at the quarterly frequency.

Grinblatt and Keloharju (2001) study the buy–sell decisions of different investor groups using a Finnish transaction-level data set, which covers a two-year period and identifies all traders. They find that institutional investors (“foreigners” in their sample) are momentum traders, consistent with the current findings on momentum investing among large traders. In the current study, the results on small traders are more complex than those on large traders, as small traders are early-stage contrarians in loser stocks but late-stage momentum traders in both winners and losers. Grinblatt and Keloharju (2001) find that individuals tend to be early-stage contrarian traders in both winners and losers, but the contrarian behavior is particularly strong with respect to past negative returns, consistent with the current study. Grinblatt and Keloharju (2001) also present evidence of late-stage momentum investing by individuals, but only among losers, as there is an increasing selling pressure in response to negative returns over the prior 4–12 months. Overall, while the focus and methodology in Grinblatt and Keloharju (2001) are somewhat different, their results are generally consistent with the current results and are another indication that the small-trader (large-trader) imbalance is a reasonable proxy for individual (institutional) trading behavior.

3. Do the Trading Pressures Translate into Price Pressures?

The preceding section found trading pressures consistent both with initial underreaction and with delayed reaction by small traders, and in particular among losers. These trading pressures might partly drive the momentum anomaly, or they might be entirely inconsequential for returns. It is difficult to establish a causal link between the delayed reaction and momentum returns, since these occur simultaneously during the holding period. However, the evidence of initial underreaction among losers provides an opportunity to test the effect of the trading pressures. That is, do the trading pressures translate into price pressures? Specifically, we would expect the losers with the highest small-trade formation-period buying pressures to have the lowest holding-period returns. This section tests this prediction.

Each month, stocks are sorted into portfolios according to prior six-month returns and prior six-month trade imbalances. For each trade-size group (small and large), formation-period imbalances are computed as the buy volume minus the sell volume over the six-month formation period, divided by the sum of the buy and sell volume. Future returns earned by these portfolios are calculated over horizons of K months, where K is equal to 1, 2–4, 2–7, 2–10, and 2–13 months. I report results based on both benchmark-adjusted and raw returns. Returns are benchmark-adjusted based on size, BM, and industry in a manner similar to the technique suggested by Grinblatt and Moskowitz (2004). Specifically, stocks are sorted into quintiles based on their year-end market capitalization and, independently, into BM quintiles. Each stock is now uniquely identified with one of the resulting 25 portfolios, and the BM- and size-adjusted return for stock i in month t over the following year is then its imbalance minus the average returns of the other stocks in the portfolio. Furthermore, returns are adjusted for industry effects as follows. Each year end, all stocks are classified by industry. The industry-adjusted return for stock i in month t over the following year is then its return minus the average of the BM- and size-adjusted returns of the other stocks in the industry. Finally, the BM-, size-, and industry-adjusted return is the return of stock i minus the BM-size benchmark return minus the industry benchmark return. If expected returns only depend on these characteristics, then the expected return of a given stock would be 0.

To ensure investability and that results are not due to bid–ask bounces, only stocks with prices of at least \$5 on the formation date are included.[17] Similar to Jegadeesh and Titman (1993), holding-period portfolio returns are calculated as the equal-weighted average of the current period's return on the K previous months' portfolios. For K equal to 2–4, for example, the portfolio return is the average of this month's return for the portfolio two months ago, this month's return for the portfolio three months ago, and this month's return for the portfolio four months ago. By averaging

[17] Specifically, low-priced stocks tend to have large percentage bid–ask spread, and since the price of a stock with, say, strong buying pressure will tend to be more often recorded at the ask, this could induce seemingly negative future returns.

across prior strategies rather than prior returns, the overlap problem is avoided and t-statistics can be computed in the normal manner.

In Table 4, stocks are first sorted into return quintiles, and then into trade imbalance quintiles. The average benchmark-adjusted returns for each of the five imbalance portfolios among winners and losers are reported, along with the difference between the benchmark-adjusted returns of the low- and high-trade imbalance portfolios. Also, the difference between the unadjusted returns of the low- and high-trade imbalance portfolios is reported (denoted *raw*). Panel A reports the results based on small-trade imbalances. No significant return difference appears in the first month after the formation date. However, over the following year, the loser portfolio with strongest small-trade selling pressure outperforms the losers with strongest small-trade buying pressure by 0.38–0.48% per month in benchmark-adjusted returns (t-statistics 2.48–3.63), depending on the holding period. This is consistent with initial underreaction among small investors (and high small-investor sentiment in those stocks), creating an upward price pressure among losers. Why is the return difference insignificant in the first month? Recall from Figure 1 that a small-trade buying pressure exists in the month following the formation date, indicating that small traders are still underreacting. Hence, the effect of initial underreaction might still have an upward effect on prices. Among winners, the return differences are generally positive, but only the raw return differences are marginally significant.[18]

Panel B of Table 4 reports the results based on large-trade imbalances. While return differences all are positive, they are relatively low at 0.05–0.25% per month, and only the $K = 2$–4 strategy among winners is significant at the 5% level.

Section 2.3 showed that the trade imbalances exhibit a marked seasonality. Table 4 shows that a similar, albeit only marginally significant, seasonality exists in returns. The bottom part of the two panels lists the returns for portfolios only invested in January, December, and February–November, respectively. Since a particularly strong selling pressure of losers exists in December, we might expect the strategy based on trading pressures to be especially profitable in January. Indeed, the results in Table 4 show that January returns based on the $K = 1$ strategy are high, but only the raw return difference of 2.49% among losers is significant with a t-statistics of 2.66. Grinblatt and Moskowitz (2004) find that returns for losers are strongly negative in December, consistent with the seasonality in trade imbalances. Table 4 shows that the $K = 1$ strategy also yields negative returns in December, though the returns again are not

[18] As an alternative risk-adjustment, the monthly raw return differences were regressed on the three Fama-French factors. The intercepts (not reported) were very similar to the average raw return differences.

Table 4
Monthly benchmark-adjusted returns for trade-imbalance portfolios within momentum portfolios

		Imbalance portfolio								
	K	1	2	3	4	5	1–5	*t*(1–5)	Raw	*t*(Raw)
Panel A: Small-trade imbalance portfolio returns										
All months										
Losers	1	–0.15	0.07	0.27	0.01	–0.32	0.17	0.93	0.26	1.25
	2–4	–0.26	–0.15	–0.13	–0.38	–0.64	0.38	2.46	0.50	2.78
	2–7	–0.28	–0.29	–0.25	–0.46	–0.76	0.48	3.28	0.57	3.40
	2–10	–0.25	–0.29	–0.28	–0.45	–0.74	0.48	3.63	0.50	3.23
	2–13	–0.21	–0.21	–0.24	–0.40	–0.63	0.42	3.23	0.45	2.97
Winners	1	0.05	–0.05	0.13	0.00	0.19	–0.14	–0.80	–0.00	–0.01
	2–4	0.46	0.33	0.28	0.22	0.44	0.02	0.15	0.17	1.05
	2–7	0.50	0.38	0.37	0.34	0.42	0.08	0.73	0.24	1.61
	2–10	0.46	0.35	0.35	0.30	0.37	0.09	0.87	0.27	1.88
	2–13	0.36	0.27	0.28	0.23	0.26	0.10	1.04	0.30	2.18
January only										
Losers	1	0.04	–0.00	1.61	1.01	–0.85	0.88	0.92	2.49	2.66
	2–4	–0.35	–0.21	0.32	–0.25	–0.42	0.07	0.13	0.19	0.26
Winners	1	–1.14	–0.46	–0.88	–1.15	–2.24	1.10	1.71	0.66	1.11
	2–4	0.08	0.56	0.17	–0.02	0.09	–0.01	–0.02	–0.15	–0.24
December only										
Losers	1	–0.33	0.07	0.09	0.35	0.61	–0.94	–1.69	–1.42	–2.14
	2–4	–0.50	0.32	0.37	0.29	–0.77	0.27	0.28	1.86	2.16
Winners	1	0.45	0.45	1.26	0.29	1.42	–0.96	–2.02	–0.70	–1.23
	2–4	–0.60	–0.47	–0.54	–0.53	–1.41	0.80	2.43	0.45	0.80
February–November										
Losers	1	–0.15	0.08	0.15	–0.12	–0.35	0.21	1.12	0.21	0.96
	2–4	–0.22	–0.19	–0.22	–0.46	–0.65	0.42	2.77	0.40	2.16
Winners	1	0.13	–0.06	0.11	0.08	0.31	–0.18	–0.94	0.00	0.01
	2–4	0.60	0.39	0.37	0.32	0.65	–0.05	–0.37	0.18	0.99

Panel B: Large-trade imbalance portfolio returns

All months										
Losers	1	–0.08	0.03	–0.03	0.19	–0.20	0.13	0.82	0.17	0.90
	2–4	–0.37	–0.25	–0.27	–0.25	–0.42	0.05	0.37	0.04	0.24
	2–7	–0.42	–0.35	–0.37	–0.37	–0.54	0.12	0.92	0.12	0.75
	2–10	–0.44	–0.33	–0.31	–0.35	–0.57	0.13	1.09	0.17	1.15
	2–13	–0.38	–0.24	–0.25	–0.28	–0.53	0.15	1.33	0.20	1.37
Winners	1	0.17	0.15	–0.07	–0.06	0.13	0.04	0.25	0.07	0.45
	2–4	0.57	0.40	0.21	0.23	0.32	0.25	2.09	0.27	2.11
	2–7	0.55	0.41	0.32	0.34	0.38	0.17	1.60	0.15	1.29
	2–10	0.51	0.36	0.29	0.33	0.33	0.18	1.80	0.19	1.75
	2–13	0.42	0.27	0.20	0.26	0.24	0.18	1.92	0.21	2.06
January only										
Losers	1	–0.44	0.22	0.91	1.31	–0.21	–0.22	–0.52	1.66	2.62
	2–4	–0.53	–0.12	–0.24	–0.03	0.03	–0.56	–1.12	–0.37	–0.80
Winners	1	–2.01	–1.61	–1.33	–0.57	–0.38	–1.63	–2.75	–0.92	–1.28
	2–4	0.22	0.42	–0.00	0.24	0.01	0.21	0.45	0.84	2.30
December only										
Losers	1	0.19	0.04	0.21	0.76	–0.41	0.60	1.53	0.29	0.50
	2–4	–0.73	–0.04	0.38	0.48	–0.40	–0.33	–0.63	1.22	2.04
Winners	1	1.02	0.51	0.97	0.50	0.77	0.26	0.41	0.12	0.20
	2–4	–1.19	–1.02	–0.48	–0.32	–0.61	–0.58	–1.75	0.17	0.42
February–November										
Losers	1	–0.07	0.01	–0.14	0.03	–0.18	0.11	0.65	0.01	0.04
	2–4	–0.32	–0.29	–0.33	–0.35	–0.47	0.15	0.98	–0.04	–0.20
Winners	1	0.30	0.29	–0.05	–0.07	0.11	0.18	1.10	0.17	0.96
	2–4	0.77	0.54	0.29	0.28	0.44	0.33	2.58	0.23	1.57

Each month in 1983–2002, NYSE/AMEX common stocks are sorted into quintiles based on past six-month returns and then into quintiles based on past six-month small-trade (panel A) or large-trade (panel B) imbalances. Stocks with strong selling (buying) pressure are in imbalance quintile 1 (5). Future monthly percentage returns are computed over holding period K. E.g., $K = 2–4$ represents average monthly returns from months two to four after the portfolio formation. The returns are computed similar to Jegadeesh and Titman (1993). Benchmark-adjusted returns (based on size, BM, and industry benchmarks) are reported for each imbalance portfolio among winners and losers, along with the difference between the benchmark-adjusted returns of imbalance portfolios 1 and 5, and its t-statistics. *Raw* denotes the difference between the unadjusted returns of imbalance portfolios 1 and 5, and $t(Raw)$ is the t-statistics of *Raw*. Average percentage returns are reported for all months, January only, December only, and February–November.

consistently significant. Finally, the table shows that the imbalance-based strategy among losers is profitable outside the turn of the year. The last part of panel A shows that the $K = 2$–4 strategy which is long the loser portfolio with strongest small-trade selling pressure and short the losers with strongest small-trade buying pressure yields 0.42% per month (t-statistics 2.77).[19]

Figures 2 and 3 showed that a strong positive correlation exists between formation-period share turnover and small-trade imbalances among losers. Therefore, a concern about the results in Table 4 could be that the small-trade imbalances proxy for turnover, and since Lee and Swaminathan (2000) show that low-turnover losers outperform high-turnover losers, the result might simply be restating the Lee and Swaminathan (2000) results. Thus, it is essential to control for turnover. Moreover, the trade imbalance measure is likely to be an incomplete proxy of the actual price pressure. In particular, a given percentage difference between buying and selling volume will likely have a stronger price effect if it arises from heavy, rather than light, trading volume. We would therefore expect the effect of trade imbalances on returns to be stronger among high-volume stocks.

Table 5 examines the effect of small-trade imbalances on returns within momentum and turnover portfolios. Specifically, stocks are sorted into quartiles based on six-month prior returns and independently into quartiles based on turnover during this period. Then, within each return-turnover portfolio, stocks are sorted into quartiles based on past six-month small-trade imbalances.[20] The results are clear: While no significant effect of small-trade imbalances on returns exists among low-turnover stocks, a strong relationship exists among high-turnover stocks.[21] Specifically, high-turnover stocks with strong selling pressure outperform high-turnover stocks with strong buying pressure among both losers and winners. For instance, the $K = 2$–7 strategy yields an average difference in benchmark-adjusted returns of 0.60% per month among high-turnover losers (t-statistics $= 2.93$) and 0.37% among high-turnover winners (t-statistics $= 1.91$). The corresponding differences in raw returns are 0.65% for both losers and winners (t-statistics 2.98 and 2.92). The $K = 2$–7 imbalance-momentum strategy which is long high-turnover winners with strong selling pressure and short high-turnover losers with strong buying

[19] The seasonality of the profitability of the strategies based on longer holding periods is not reported in Table 4 (for shortness of exposition). However, the February–November average returns were in all cases very similar to the returns based on the full sample.

[20] The number of portfolios was chosen to ensure a reasonable number of stocks in each portfolio. The average numbers of stocks in the low-turnover imbalance portfolios were 22 and 18 for the losers and winners, while the high-turnover loser and winner portfolios had an average of 29 and 30, respectively.

[21] Sorts based on large-trade imbalances within momentum-turnover portfolios did not yield any return differences significant at the 5% level (not reported), consistent with the results on Table 4B.

Table 5
Monthly benchmark-adjusted returns for small-trade imbalance portfolios within momentum and turnover portfolios

	K	Imbalance portfolio 1	2	3	4	1–4	t(1–4)	Raw	t(Raw)
Low-turnover stocks									
Losers	1	0.12	0.05	0.30	0.25	–0.13	–0.52	–0.06	–0.24
	2–4	–0.31	–0.05	–0.31	–0.26	–0.05	–0.23	0.02	0.11
	2–7	–0.30	–0.15	–0.38	–0.31	0.01	0.05	0.11	0.57
	2–10	–0.29	–0.15	–0.33	–0.35	0.06	0.38	0.12	0.71
	2–13	–0.23	–0.11	–0.28	–0.31	0.09	0.58	0.15	0.97
Winners	1	–0.16	0.06	0.06	0.08	–0.24	–1.11	–0.21	–0.98
	2–4	0.40	0.45	0.34	0.73	–0.33	–1.74	–0.23	–1.16
	2–7	0.46	0.47	0.50	0.69	–0.23	–1.42	–0.19	–1.18
	2–10	0.42	0.47	0.45	0.64	–0.22	–1.58	–0.23	–1.69
	2–13	0.36	0.35	0.35	0.49	–0.13	–0.98	–0.14	–1.08
High-turnover stocks									
Losers	1	–0.28	–0.05	–0.30	–0.88	0.60	2.50	0.70	2.57
	2–4	–0.40	–0.30	–0.59	–1.02	0.62	2.93	0.73	3.05
	2–7	–0.51	–0.41	–0.55	–1.10	0.60	3.14	0.65	2.98
	2–10	–0.42	–0.43	–0.55	–1.01	0.58	3.36	0.60	3.05
	2–13	–0.32	–0.36	–0.45	–0.83	0.51	3.12	0.51	2.69
Winners	1	–0.04	0.31	0.12	0.16	–0.21	–0.85	0.02	0.08
	2–4	0.38	0.33	0.00	0.13	0.26	1.18	0.52	2.16
	2–7	0.48	0.35	0.17	0.11	0.37	1.91	0.65	2.92
	2–10	0.43	0.28	0.10	0.06	0.37	2.16	0.67	3.25
	2–13	0.34	0.17	0.04	–0.05	0.39	2.47	0.69	3.52

Each month in 1983–2002, NYSE/AMEX common stocks are sorted into quartiles based on past six-month return and independently into quartiles based on past six-month share turnover. Within return-turnover portfolios, stocks are then sorted into quartiles based on past six-month small-trade imbalances. Results are reported for low- and high-turnover losers and winners. Stocks with strong selling (buying) pressure are in imbalance quartile 1 (4). Future monthly percentage returns are computed over holding period K. E.g., $K = 2$–4 represents average monthly returns from months two to four after the portfolio formation. The returns are computed similar to Jegadeesh and Titman (1993). Benchmark-adjusted returns (based on size, BM, and industry benchmarks) are reported for each imbalance portfolio among high- and low-turnover winners and losers, along with the difference between the benchmark-adjusted returns of imbalance portfolios 1 and 4 and its t-statistics. *Raw* denotes the difference between the unadjusted returns of imbalance portfolios 1 and 4, and t(*Raw*) is the t-statistics of *Raw*.

pressure yields an average benchmark-adjusted return of 1.58% [0.48 – (−1.10)] per month.[22]

Table 5 showed that turnover does not explain the effect of small-trade imbalance on returns. Rather, conditioning also on turnover enhances the profitability across imbalance-momentum strategies. Conversely, do trade imbalances explain the effect of turnover on returns? To address this question, the sorting order was reversed, such that stocks were first sorted independently into quartiles according to past six-month returns

[22] Results using other formation periods are not reported to conserve space. However, using a three-month formation period results in marginally weaker return differences, while the differences tend to be marginally stronger using a 12-month formation period. For instance, when sorting based on past 12-month returns, turnover and small-trade imbalance, the difference between the average characteristic-adjusted returns of high-turnover/selling-pressure winners and high-turnover/buying-pressure winners is significant at the 5% level over all holding periods after the month following the formation date.

and small-trade imbalances, and then into quartiles according to past six-month turnover. The results in Table 6 show that turnover has no significant effect on future returns among stocks with strong small-trade selling pressure (imbalance quartile 1). However, among stocks with strong small-trade buying pressures (imbalance quartile 4), low-turnover stocks significantly outperform high-turnover stocks, both among winners and losers. For instance, among low-imbalance losers, the return difference between low-and high-turnover stocks in the $K = 2–7$ strategy is an insignificant 0.19% per month (t-statistics = 0.73), while among high-imbalance losers, high-turnover stocks underperform low-turnover stocks by 0.77% per month (t-statistics = 2.37). In other words, if high volume arises in connection with buying-related activity among small traders, the stock subsequently underperforms, while if the volume arises in connection with selling-related activity, the stock does not

Table 6
Monthly benchmark-adjusted returns for turnover portfolios within momentum and small-trade imbalance portfolios

		Turnover portfolio							
	K	1	2	3	4	1–4	*t*(1–4)	Raw	*t*(Raw)
Selling-pressure stocks									
Losers	1	0.20	–0.20	–0.13	–0.28	0.48	1.53	0.57	1.76
	2–4	–0.30	0.11	–0.14	–0.49	0.19	0.71	0.26	0.93
	2–7	–0.30	–0.00	–0.17	–0.48	0.19	0.73	0.31	1.14
	2–10	–0.29	–0.05	–0.17	–0.36	0.07	0.30	0.18	0.70
	2–13	–0.24	–0.07	–0.08	–0.26	0.02	0.09	0.12	0.47
Winners	1	–0.23	–0.04	0.24	0.19	–0.43	–1.75	–0.55	–2.11
	2–4	0.46	0.40	0.36	0.46	0.00	0.01	–0.13	–0.51
	2–7	0.52	0.34	0.46	0.54	–0.02	–0.08	–0.20	–0.81
	2–10	0.49	0.30	0.45	0.45	0.04	0.19	–0.16	–0.67
	2–13	0.42	0.27	0.34	0.35	0.07	0.35	–0.07	–0.29
Buying-pressure stocks									
Losers	1	0.40	0.14	–0.33	–1.10	1.50	4.13	1.71	4.45
	2–4	–0.28	–0.18	–0.61	–0.96	0.68	1.97	0.82	2.18
	2–7	–0.27	–0.39	–0.66	–1.04	0.77	2.37	0.83	2.34
	2–10	–0.28	–0.39	–0.69	–0.92	0.63	2.01	0.64	1.88
	2–13	–0.29	–0.38	–0.59	–0.75	0.46	1.53	0.46	1.40
Winners	1	0.18	0.00	0.35	0.13	0.05	0.15	0.19	0.57
	2–4	0.60	0.46	0.27	0.06	0.55	2.06	0.67	2.24
	2–7	0.56	0.50	0.28	0.05	0.52	2.20	0.67	2.48
	2–10	0.56	0.48	0.20	0.01	0.55	2.41	0.74	2.84
	2–13	0.43	0.41	0.16	–0.09	0.52	2.27	0.72	2.78

Each month in 1983–2002, NYSE/AMEX common stocks are sorted into quartiles based on past six-month return and independently into quartiles based on past six-month small-trade imbalance. Within return-imbalance portfolios, stocks are then sorted into quartiles based on past six-month share turnover. Results are reported for the losers and winners with the strongest selling and buying pressures (i.e., imbalance portfolios 1 and 4). Low-turnover (high-turnover) stocks are in turnover quartile 1 (4). Future monthly percentage returns are computed over holding period K. E.g., $K = 2–4$ represents average monthly returns from months two to four after the portfolio formation. The returns are computed similar to Jegadeesh and Titman (1993). Benchmark-adjusted returns (based on size, BM, and industry benchmarks) are reported for each imbalance portfolio among high- and low-imbalance winners and losers, along with the difference between the benchmark-adjusted returns of turnover portfolios 1 and 4 and its t-statistics. *Raw* denotes the difference between the unadjusted returns of turnover portfolios 1 and 4, and t(*Raw*) is the t-statistics of *Raw*.

underperform in subsequent months. This supports and refines the notion in Lee and Swaminathan (2000) that volume could be a sentiment indicator. That is, the stocks that subsequently underperform are the ones predicted by both volume and small-trade imbalances to be favored by investor sentiment: High-turnover stocks with strong buying pressures underperform both high-turnover stock with strong selling pressures and low-turnover stocks with strong buying pressures. On the other hand, if turnover and small-trade imbalance do indeed proxy for investor sentiment, then the above results indicate that *negative* investor sentiment does not significantly affect returns. This supports the suggestion in Miller (1977) that rational arbitrageurs can take long positions to take advantage of low investor sentiment, preventing those stocks from being severely underpriced, while short-selling constraints may prevent arbitrageurs to take advantage of high sentiment.

4. Conclusion

This article provides a trade-based analysis of momentum. If momentum is driven by some particular kind of investor behavior, we should be able to detect such a behavior. Indeed, using transactions data to measure buying and selling pressures for losers and winners, I show evidence consistent with both initial underreaction and delayed reaction among small traders, but not among large traders. Specifically, for losers, there is an initial small-trade buying pressure, which gradually converts into an intense selling pressure over the following year. For winners, there is similarly a mounting small-trade buying pressure during the six months following the formation date. By contrast, initial selling pressure for losers and buying pressure for winners exist among large trades. These large-trade imbalances gradually diminish and disappear around one year after the formation date.

The trading pressures appear to translate into price pressures. Sorting momentum stocks into portfolios based on formation-period trading pressures, I find that losers with strong small-trade buying pressures underperform losers with selling pressures over the subsequent year. By contrast, sorting into portfolios based on large-trade imbalances does not yield significant differences in future returns.

Both the small-trade imbalances and the return differences are particularly strong among high-volume stocks. These results are generally consistent with the suggestion of Lee and Swaminathan (2000) that volume provides information about the extent to which investor sentiment favors a stock at a point in time. Moreover, the ability of volume to predict future returns is absent among stocks with high small-trade selling pressures, but strong among stocks with high small-trade buying pressures.

The results underline the heterogeneity of the trader population. Small investors appear to trade very differently from larger investors, and the evidence presented here points toward the trading behavior of smaller investors as a source of the momentum effect. While the results are consistent with an explanation of momentum based on the behavior of a set of investors whom we might suspect most susceptible to behavioral biases, the results do not unambiguously support any one of the extant theoretical models, which do not assign any particular role to small or individual investors. It is the hope that the current results can be of help in directing future theoretical research. Likewise, by suggesting trade imbalances as an alternative metric for analyzing investor reaction to some event, the approach taken here can potentially help distinguishing between different explanations of other return anomalies.

Appendix: Trade and quote filters

Trades and quotes in the ISSM/TAQ data sets are reported with a *condition code*. For instance, "C" indicates a cash sale (same day clearing). However, not all condition codes have the same meaning in the two data sets. Trades and quotes with the following condition codes are excluded from the analysis:

	ISSM	TAQ
Trades	C, L, N, R, O, Z	A, C, D, G, L, N, O, R, X, Z, 8, 9
Quotes	D, G, I, P, S, V, X, Z	4, 5, 7–9, 11, 13–17, 19, 20

Moreover, TAQ trades with a *correction code* greater than 1 are excluded. All codes are explained in the ISSM and TAQ manuals [ISSM (1992); TAQ (2003)].

Only NYSE/AMEX quotes are used, and possible errors are excluded. Specifically, quotes are deleted if the ask price is not greater than the bid price, or the bid–ask spread is greater than 75% of the midquote, or the ask (bid) price is more than double or less than half of the previous ask (bid) price. Trades are assumed to have occurred five seconds before being reported, as in Lee and Ready (1991). Only trades which are reported within the opening hours of the exchanges are included. Trades at prices of more than double or less than half of the previous trade are excluded.

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