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Buyers versus Sellers: Who Initiates Trades, and When?

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Abstract

Models that examine investors' motivations to trade often make opposite predictions about the relation between trading decisions and past returns. We find that, in the aggregate, both buyer- and seller-initiated trades increase with past returns. The difference between buyer- and seller-initiated trades is negatively related to short horizon returns but positively related to returns over longer horizons. Tax-loss-related seller-initiated trades in December and January are accompanied by increased buyer-initiated trades. Past returns significantly affect trading decisions, and these findings are consistent with a number of different models of trading behavior.

I. Introduction

Academics and practitioners have long been keenly interested in how observable factors such as past returns and stock characteristics affect order flows from buyers and sellers. Order flows convey value-relevant information to the market and play an important role in price discovery. Predictable changes in order flows do not convey new information, and an understanding of the factors related to such changes would help in efficiently extracting information. Similarly, portfolio managers will likely face less adverse price impacts if they time their orders to trade against expected order flows. In general, a good understanding of the factors that affect the direction of order flow provides important insights into the factors that affect investors' trading decisions, time variation in trading volume, and expected price impacts of buy and sell trades.

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Many behavioral hypotheses proposed in the literature predict that past returns will be related to investors' decisions to buy or sell, although they make conflicting predictions about the sign of such relations. For example, the disposition effect predicts that investors are more likely to sell winners and predicts a negative relation between past returns and order flows. Other hypotheses, such as momentum trading hypotheses (see Jegadeesh and Titman (1993)), predict an opposite relation between past returns and order flows because momentum investors are more likely to buy winners (stocks with high past returns) and sell losers (stocks with low past returns). Tax-induced trading hypotheses and contrarian trading hypotheses also predict that order flows would be related to past returns.

Empirical analysis of investors' trading decisions in the literature finds mixed evidence. (We discuss this in more detail in Section II.A.) These empirical studies typically examine the holdings of subsets of investors and examine their trading behavior. In contrast, our paper examines aggregate trading behavior, and we separately examine the factors that affect buying and selling decisions. Although the subset analysis in the literature is informative about particular groups of investors, an aggregate analysis is necessary to gain insights into any systematic pattern in aggregate trade flows and their potential impact on asset prices. The determinants of aggregate trading behavior cannot be established based on the evidence in the literature about the trading patterns of subsets of investors. The trading behaviors of a subset of investors need not generalize to the aggregate level because the trading activity of this subset may not be sufficiently pervasive.

Statman, Thorley, and Vorkink (2006) examine the relation between turnover and past returns to test the impact of the disposition effect at the aggregate level. In contrast, we use buyer- and seller-initiated trades in our tests because the underlying hypotheses make predictions about when buyers or sellers would initiate trades and not about turnover per se. Without knowing whether a buyer or a seller initiated the trade, it is hard to interpret any relation between trading volume/turnover and past returns as being consistent with any particular theory. For instance, Statman et al. find that turnover is positively related to past returns and conclude that this evidence supports the disposition effect, but this inference assumes that differences in turnover across winner and loser stocks are driven by seller-initiated trades. This evidence could well be interpreted as evidence of momentum trading rather than evidence of the disposition effect if one were to assume that buyers, rather than sellers, initiate trades for past winners. In fact, our results indicate that momentum trading contributes more to the increased turnover than does the disposition effect at longer horizons.

We examine the relation between buys, sells, net trades (buys minus sells), and past returns over various horizons at the aggregate level. When multiple hypotheses affect individual trading behavior, the aggregate effect captures the net effect of these hypotheses. The net effect at the aggregate level could be different at different horizons and could be different for buys, sells, and net trades because the relative impact of the hypotheses could vary. The implications of the individual hypotheses that contribute to the aggregate effect are the following:

1) Disposition effect: Sellers are more likely to initiate trades for past winners (stocks with positive past returns) than for past losers (stocks with negative past returns).

2) Tax-induced trading: Sellers are more likely to initiate trades for losers than for winners.

3) Seasonal tax-induced trading: Sellers are more likely initiate trades for losers than for winners in December but more likely to initiate trades for winners in January.

4) Momentum trading: Buyers are more likely to initiate trades for winners, and sellers are more likely to initiate trades for losers.

5) Contrarian trading: Buyers are more likely to initiate trades for losers, and sellers are more likely to initiate trades for winners.

Our empirical findings indicate that the relative importance of these hypotheses is different for buys and sells, and it varies across return horizons. Investors are more likely to initiate buy trades for 1-month losers than for 1-month winners. For horizons longer than 2 months, investors are more likely to initiate buy trades for stocks with higher returns than for those with lower returns. For buys, investors tend to be short-term contrarians but long-term momentum traders. Investors are less likely to initiate sells for 1-month losers than for 1-month winners. For horizons longer than 2 months, investors are more likely to initiate sells for winners than for losers. Thus, investors tend to be contrarians for both buys and sells at the 1-month horizon. However, for longer horizons, momentum trading is relatively more important for buys, but the disposition effect or contrarian trading is relatively more important for sells.

Net trades (buys minus sells) are negatively related to 1- and 2-month lagged returns but positively related to returns at 4- to 12-month lags. Net trades suggest that, in aggregate, momentum trades are relatively more important than contrarian or disposition trades in the long term, whereas the reverse is true in the short term. Overall, the relative impacts of the hypotheses we examine are different for buys and sells, and they vary over return horizons.

When we examine seasonal patterns, we find that investors tend to sell past losers in December, which is consistent with the evidence of the year-end tax-loss selling hypothesis. We also find that investors are more likely to sell winners in January, which enables them to defer the realization of capital gains from the previous year. This evidence is consistent with the findings of Lakonishok and Smidt (1986), who note that the turnover for losers increases in December, and the turnover for winners increases in January.

The tax-loss selling hypothesis has been used to explain the well-documented anomaly that past losers, particularly small firms, earn abnormal returns in January (e.g., Reinganum (1983), Schultz (1985)). This explanation posits that the tax-loss selling pressure in December depresses the prices of losers, which later rebound in January. Constantinides (1984), however, argues that the selling pressure should not lead to price pressure because other investors will step in to take advantage of any mispricing, and any selling pressure would attract offsetting buying pressure. Because we separately examine the determinants of aggregate buys and sells, we are able to address such nuances in the tax-loss selling hypothesis. We find larger buyer-initiated trades for losers in December and for winners in January. Therefore, the increased selling pressure for losers is at least partially offset by buyer-initiated trades, which is consistent with Constantinides's argument.

II. Determinants of Buy and Sell Order Flows

A. Literature Review

Investors may base their decisions on past returns for behavioral reasons or because they rationally extract information from returns. Shefrin and Statman (1985) propose the disposition effect, which posits that investors tend to realize gains but postpone loss realization. Therefore, the disposition effect predicts that sellers are more likely to initiate trades for winners than for losers.

Brennan and Cao (1997) and Hong and Stein (1999) find that uninformed investors rationally extract informed investors' signals from price changes and trade in the same direction as past returns. These models predict more buyer-initiated trades for past winners and more seller-initiated trades for past losers, which we refer to as the momentum trading hypothesis. In contrast, De Long, Shleifer, Summers, and Waldmann (1990) predict that when some investors trade based on signals unrelated to fundamentals, rational investors would optimally be contrarian traders and buy losers and sell winners.

Investors may also trade for tax reasons. Constantinides (1984) shows that if there were no trading costs or limits on capital loss deductions, investors should optimally sell all stocks that experience capital losses immediately, and they should not sell their winners. If investors follow this policy, they are more likely to initiate trades for losers than for winners, and this implication is the opposite of the disposition effect. However, because of trading costs and limits on capital loss deductions, investors would not continuously follow such a strategy, and any tax-induced trading is likely to be concentrated around the turn of the year (see Lakonishok and Smidt (1986)). Under this seasonal tax-loss selling hypothesis, investors are more likely to sell past losers than winners in December to realize capital losses, and they are more likely to defer the realization of capital gains and sell winners in January.

Several papers test the predictions of these models for individual and institutional investors. Odean (1998) uses individual investors' trading account data and finds support for the disposition effect. Ben-David and Hirshleifer (2012) use similar data but report that the likelihood of selling as a function of profit is V-shaped, and the likelihood also depends on the holding period. They conclude that there is "no general evidence that individual investors in U.S. stocks have an inherent preference or 'disposition' to realize winner stocks or a direct reluctance to realize loser stocks" (see Ben-David and Hirshleifer (2012), p. 2522). Thus, these two papers offer mixed support for the disposition effect. Barber and Odean (2002), Grinblatt and Keloharju (2000), and Kaniel, Saar, and Titman (2008) find evidence of contrarian trading by individual investors in the United States. However, Ng and Wu (2007) find evidence of momentum trading by wealthy individuals in China.

Several other studies examine institutional trades and find mixed support for some of the momentum trading hypotheses. Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), and Sias (2004) report evidence of momentum trading. However, Gompers and Metrick (2001) and de Haan and Kakes (2011) find that institutions are contrarian traders. On the other hand, Lakonishok, Shleifer, and Vishny (1992) find that institutions follow neither momentum nor contrarian trading. Given the mixed evidence, we focus on trading behavior at the aggregate level.

B. Aggregate Effects on Order Flows with Heterogeneous Traders

The theories of trading decisions typically examine one set of issues at a time and make predictions about how each set of issues individually affects investors' decision to trade. However, many factors simultaneously influence investors' trading decisions, and the extent to which each of these factors affects trading decisions may differ across investors. Investors whose trades are influenced by past returns may trade with other investors whose trades are based on inside information or with other traders who may trade randomly or to meet personal liquidity needs. Moreover, returns over different horizons may affect the trading decisions of different investors.

We present a reduced-form model that allows for such heterogeneity among traders and derives empirically testable implications. The model shows that even if returns at different horizons affect the trading decisions of different investors, we can infer the net effect of returns at a particular horizon on order flows using simple multivariate regressions. We outline the model and main results here. The Internet Appendix (available at www.jfqa.org) presents the details and all the proofs.

In our model, there are heterogeneous sets of active investors who initiate buy and sell trades. The net orders from these active investors are filled by passive market makers, following Kyle (1985). Suppose S_T is a signal that is a monotonically increasing function of past returns. Also suppose there are N_M momentum traders, N_C contrarian traders, and N_D disposition traders. The likelihood that a momentum trader will initiate a buy trade or a sell at time T increases in S_T, and the opposite is true for contrarian traders. For the disposition traders, the likelihood of a sell increases in S_T, but their buys are not related to this signal. For all of these traders, the decision to trade may also depend on other signals that are orthogonal to S_T.

There are also other active traders in the economy whose trading decisions are uncorrelated with past returns. These traders use signals orthogonal to S_T, which could also include private information. Let there be N_O such other traders, and let ε_i denote the supplementary signal that is orthogonal to S_T. Consider the slope coefficient in a regression of, for example, BUYS_T on S_T, given by $\beta_{\text{BUYS}} = \text{cov}(\text{BUYS}_T, S_T)/\text{var}(S_T)$. The following proposition shows that we can infer the net effect of the hypotheses from the sign of β_{BUYS}.

Proposition 1. The sign of the slope coefficient β in a regression of BUYS, SELLS, or BUYS − SELLS on the signal (and hence past returns) depends on the relative number of momentum, contrarian, and disposition traders. In particular:

$$\begin{aligned}
\beta_{\text{BUYS}} &> 0 \quad \text{iff} \quad N_M > N_C; \\
\beta_{-\text{SELLS}} &> 0 \quad \text{iff} \quad N_M > N_C + N_D; \\
\beta_{\text{BUYS}-\text{SELLS}} &> 0 \quad \text{iff} \quad N_M > N_C + 0.5N_D.
\end{aligned}$$

As we discussed at the outset, we cannot infer the net effect of these hypotheses from the relation between turnover and past returns, as we formally show in the following proposition:

Proposition 2. The sign of the regression slope coefficient of turnover on past returns is independent of the number of momentum and contrarian traders.

So far, the model does not specify the horizon that investors use to measure past returns, which is consistent with the underlying theories. But in practice, different investors are likely to use returns over different horizons in their trading decisions. The following proposition generalizes the model to allow for heterogeneity in past return horizons across investors:

Proposition 3. Suppose S_{T1} and S_{T2} are signals correlated with 1- and 2-period lagged returns, respectively. Suppose there are N_{M1} momentum traders who use S_{T1} and N_{M2} momentum traders who use $S_{T1}+S_{T2}$ in their trading decisions. Let N_{C1} and N_{C2} be the analogous number of contrarian traders. Suppose we fit the following multivariate regression:

$$\text{BUYS}_T \quad = \quad a+\beta_1 S_{T1}+\beta_2 S_{T2}+v_T.$$

Then:

$$\begin{array}{llll} \beta_1 > 0 & \text{iff} & (N_{M1}+N_{M2}) > (N_{C1}+N_{C2}), \\ \beta_2 > 0 & \text{iff} & N_{M2} > N_{C2}. \end{array}$$

Analogous relations are obtained for $-$SELLS and BUYS $-$ SELLS.

III. Data

Our tests examine the determinants of buys, sells, and the difference between buys and sells, which we construct using Trade and Quote (TAQ) data. In addition to TAQ data, we also use data from Center for Research in Security Prices (CRSP) and Compustat. Our main sample comprises common stocks listed on the New York Stock Exchange (NYSE) in the period from Jan. 1993 to Dec. 2010. The sample comprises all stocks that satisfy the following criteria in any given month: i) The return data for the current month and over at least the past 12 months are available from CRSP, ii) sufficient data are available to calculate market capitalization at the end of the previous month, iii) book value data are available from Compustat as of the previous calendar year ending, and iv) intraday transactions data for the current month and over the previous 3 months are available on TAQ. We include only common stocks with CRSP share codes of 10 or 11. There are 1,482 stocks per month on average that satisfy all of the criteria. For robustness checks, we also use NASDAQ data over the period 1987 through 1996 in addition to the NYSE stocks. The advantage of using this sample is that we know that during this period, market makers took the passive side of trades initiated on NASDAQ by investors, much like the setting in the market microstructure models.

The TAQ data set reports intraday quotes and the prices and quantity of each trade. We use the filtering rules of Chordia, Roll, and Subrahmanyam (2001) to eliminate obvious data errors in the TAQ data set. We then use the Lee and Ready

(1991) algorithm to classify transactions as either a buy or a sell. Briefly, we implement the Lee and Ready algorithm as follows: If a trade is executed at a price above (below) the quote midpoint, we classify it as a buy (sell); if a trade occurs exactly at the quote midpoint, we sign it using the previous transaction price according to the tick test (i.e., a buy if the sign of the last nonzero price change is positive, and vice versa). The Lee and Ready algorithm uses the fact that seller-initiated trades tend to execute at a lower price than buyer-initiated trades. We apply the tick test up to the past five price changes. If the past five price changes are 0, then we do not use the trade in the computation of buys or sells. As Lee and Ready (1991) note, the time stamps on quotes are not always correctly synchronized with those for trades, and hence they recommend that the quotes be matched to trades with a 5-second delay. We follow this 5-second-delay rule until 1998. Because such recording errors are not observed in the more recent data (see Chordia, Roll, and Subrahmanyam (2005)), we do not impose any delays after 1998.

Lee and Radhakrishna (2000) and Odders-White (2000) examine the trade-level accuracy of the Lee and Ready (1991) algorithm for NYSE-traded stocks and report accuracy rates of 93% and 85%, respectively. Ellis, Michaely, and O'Hara (2000) report an accuracy rate of 81% for NASDAQ stocks. Chakrabarty, Moulton, and Shkilko (2012) examine a postdecimalization period and find the transaction-level accuracy of the Lee and Ready algorithm to be about 68% for NASDAQ stocks. What is important from the perspective of our study, however, is not the trade-level accuracy but the accuracy when trade-level classifications are aggregated. For example, even if some seller-initiated trades on a particular day are misclassified as buyer-initiated trades and similar numbers of buyer-initiated trades are also misclassified, then daily-level accuracy would be much greater than trade-level accuracy. In fact, Chakrabarty et al. find that the daily-level error rate is close to 0 and statistically insignificant. Therefore, any trade-level misclassification is unlikely to meaningfully impact our tests based on aggregated data.

Once we classify each trade as a buy or a sell, we aggregate over each month to compute monthly BUYS and SELLS. We normalize monthly BUYS and SELLS by the average monthly trading volume over the past 12 months (i.e., months $t-1$ to $t-12$).[1] The literature typically normalizes trades by summation of contemporaneous BUYS and SELLS rather than by average past trading volume. For example, we can define order imbalance as $(\text{BUYS}_{i,t}-\text{SELLS}_{i,t})/(\text{BUYS}_{i,t}+\text{SELLS}_{i,t})$. Under this definition, BUYS, SELLS, and order imbalance convey identical information because $(\text{BUYS}_{i,t}-\text{SELLS}_{i,t})/(\text{BUYS}_{i,t}+\text{SELLS}_{i,t}) = 2\times\text{BUYS}_{i,t}/(\text{BUYS}_{i,t}+\text{SELLS}_{i,t})-1 = -2\times\text{SELLS}_{i,t}/(\text{BUYS}_{i,t}+\text{SELLS}_{i,t})+1$. Because we propose to separately examine the impact of past returns on BUYS, SELLS, and BUYS − SELLS, we use average trading volumes to normalize these measures of trades. In a previous version, we normalized the order imbalance by the contemporaneous trading volume and obtained results similar to those presented here.

[1]We also find similar results when we use average monthly trading volume over the previous 6, 18, or 24 months.

We conduct our analysis in terms of both the number of trades and the number of shares traded. In typical market microstructure models, such as Kyle's (1985) model, traders' information is revealed by the number of shares they trade. However, Jones, Kaul, and Lipson (1994) find that, empirically, the number of shares traded does not contain incremental information relative to number of trades. Therefore, we use both measures. When BUYS and SELLS are measured in terms of number of trades, we assign the same weight to a trade regardless of trade size; hence, a small trade will get the same weight as a large trade using this measure.

Table 1 presents the summary statistics for BUYS and SELLS. All summary statistics are time-series averages of the corresponding statistics in the cross section each month. On average, there are 1,482 stocks per month for which these statistics are calculated. The mean (median) for BUYS – SELLS is 4.4% (3.8%)

TABLE 1

Descriptive Statistics for NYSE Stocks

Table 1 presents descriptive statistics on the key variables. We measure BUYS and SELLS both in number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., month $t-1$ to $t-12$). All summary statistics are reported as the time-series averages of monthly cross-sectional measures. Each month, a stock is classified as a small (big) stock if its market capitalization is lower (higher) than the median market capitalization that month. Each month, a stock is classified as a growth (value) stock if its book-to-market ratio is lower (higher) than the median book-to-market ratio that month. Panels B through E report the statistics for these subsamples of firms. The sample includes all NYSE stocks over the period 1993–2010.

	Mean	Median	Std. Dev.	Skewness	Kurtosis
Panel A. All Stocks					
BUYS (number)	0.598	0.556	0.297	4.894	77.053
SELLS (number)	−0.555	−0.521	0.238	−4.843	74.503
BUYS – SELLS (number)	0.044	0.038	0.141	1.455	43.289
BUYS (shares)	0.575	0.509	0.366	5.730	87.264
SELLS (shares)	−0.535	−0.466	0.356	−6.610	103.858
BUYS – SELLS (shares)	0.040	0.042	0.219	−1.621	97.438
Panel B. Small Stocks					
BUYS (number)	0.585	0.522	0.361	4.459	51.213
SELLS (number)	−0.551	−0.501	0.289	−4.224	47.150
BUYS – SELLS (number)	0.034	0.024	0.169	1.455	31.662
BUYS (shares)	0.559	0.467	0.434	5.050	59.026
SELLS (shares)	−0.547	−0.455	0.431	−5.490	65.258
BUYS – SELLS (shares)	0.013	0.016	0.276	−1.329	64.648
Panel C. Big Stocks					
BUYS (number)	0.612	0.580	0.209	2.818	27.754
SELLS (number)	−0.560	−0.535	0.169	−3.156	34.221
BUYS – SELLS (number)	0.052	0.046	0.107	0.528	15.907
BUYS (shares)	0.589	0.535	0.276	4.045	43.388
SELLS (shares)	−0.526	−0.474	0.261	−4.941	58.904
BUYS – SELLS (shares)	0.063	0.058	0.144	−0.267	40.869
Panel D. Growth Stocks					
BUYS (number)	0.633	0.586	0.282	4.212	50.588
SELLS (number)	−0.571	−0.534	0.226	−4.304	50.648
BUYS – SELLS (number)	0.062	0.053	0.129	1.347	32.174
BUYS (shares)	0.602	0.536	0.334	4.633	52.290
SELLS (shares)	−0.543	−0.478	0.322	−5.502	67.082
BUYS – SELLS (shares)	0.059	0.056	0.181	−1.288	60.743
Panel E. Value Stocks					
BUYS (number)	0.569	0.528	0.287	3.928	45.212
SELLS (number)	−0.542	−0.509	0.234	−3.861	43.492
BUYS – SELLS (number)	0.028	0.022	0.144	0.968	26.578
BUYS (shares)	0.551	0.483	0.368	4.818	56.646
SELLS (shares)	−0.528	−0.456	0.365	−5.351	63.764
BUYS – SELLS (shares)	0.023	0.027	0.236	−1.091	62.743

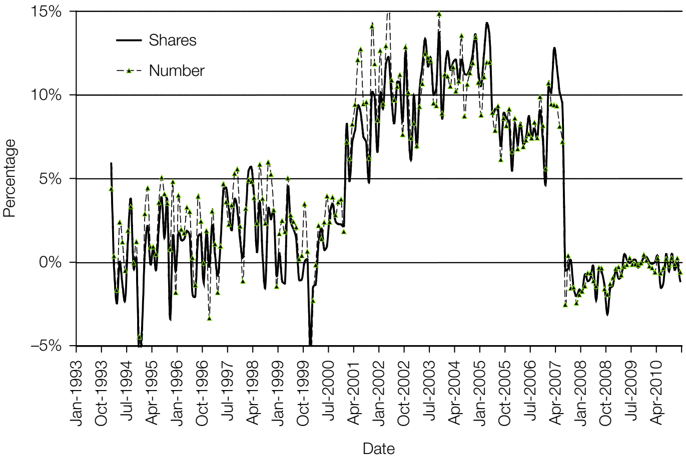
in number of trades and 4.0% (4.2%) in shares traded. Therefore, on average, there are more buyer-initiated trades than seller-initiated trades. In order to ascertain whether there are differences in these statistics across different kinds of stocks, we also calculate them for certain subsamples. Each month, we divide the sample of stocks into small and big stocks based on whether their market capitalization is smaller or larger than the median market capitalization at the beginning of that month. We follow a similar procedure to classify stocks into growth and value stocks based on their book-to-market ratios. Panels B–E of Table 1 present the descriptive statistics for these stocks. We note that BUYS − SELLS are higher for big stocks than for small stocks and higher for growth stocks than for value stocks.

Figure 1 presents the equal-weighted average of BUYS − SELLS over time.[2] In general, BUYS are higher than SELLS, except for a few months in the early part of the sample period and in the period starting in the latter half of 2007. Figure 1 also indicates that there is no appreciable difference in BUYS − SELLS with number of trades or shares traded.

FIGURE 1

BUYS − SELLS over Time for NYSE Stocks

We measure BUYS and SELLS both in number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., month $t-1$ to $t-12$). Figure 1 shows the cross-sectional equal-weighted average of BUYS − SELLS over time. The sample includes all NYSE stocks over the period 1993–2010.



[2]Note that for purposes of presentation, some observations have been trimmed. Three observations that were trimmed for number of trades had values of −5.09% (Dec. 1994), −7.23% (Dec. 1999), and 15.79% (Apr. 2002). One observation that was trimmed for shares traded had value of −5.93% (Jan. 1994). These dates do not seem to coincide with any particularly noteworthy market events.

IV. Empirical Tests and Results

The hypotheses that predict a relation between trading decisions and past returns do not specify the horizons over which returns affect trading. For instance, the theories suggest that investors take into account the prices at which they bought the stocks when they decide to trade, but different investors buy stocks at different points in time. In practice, both individuals and institutions have widely varying investment horizons. As Proposition 3 shows, even with such heterogeneity, we can determine the impact of returns at various horizons on investors' trading decisions using multivariate regressions with lagged monthly returns.

We fit the following cross-sectional regression to determine the marginal impact of past returns over the previous 12 months:

$$
\begin{aligned}
(1) \qquad Y_{i,t} \quad = \quad & a_t + \sum_{j=1}^{12} b_{t,j}\mathrm{RET}_{i,t-j} + c_t \ln\left(\mathrm{SIZE}_{i,t-1}\right) + d_t \ln\left(\mathrm{BM}_{i,t-1}\right) \\
& + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{3} f_{t,j} Y_{i,t-j} + u_{i,t},
\end{aligned}
$$

where $Y_{i,t}$ is $\mathrm{BUYS}_{i,t}$, $-\mathrm{SELLS}_{i,t}$, or $\mathrm{BUYS}_{i,t} - \mathrm{SELLS}_{i,t}$. We include the following control variables in the regression: $\ln(\mathrm{SIZE}_{i,t-1})$ is the natural logarithm of market capitalization of equity at the end of month $t-1$; $\ln(\mathrm{BM}_{i,t-1})$ is the natural logarithm of book-to-market ratio at the end of month $t-1$; and $\mathrm{VOL}_{i,t-1}$ is the standard deviation of stock i returns, which we compute using daily returns in month $t-1$. We use $-$SELLS as the dependent variable (i.e., SELLS multiplied by -1) so that the signs of the slope coefficients are directly comparable with those in the BUYS $-$ SELLS regression. We include size and book-to-market as control variables because of cross-sectional differences in order imbalances between different kinds of stocks, as evidenced by the descriptive statistics in Table 1.

The regression in equation (1) also includes lagged dependent variables as controls. For instance, the control variables are lagged BUYS when BUYS is the dependent variable and are lagged $-$SELLS when $-$SELLS is the dependent variable. Therefore, the slope coefficients for the BUYS $-$ SELLS regression are not the sum of the corresponding slope coefficients from BUYS and $-$SELLS regressions because the lagged dependent variables differ across the three specifications.

The lagged dependent variables capture the persistence in order flows that are unrelated to past returns.[3] Harris and Raviv (1993) and Wang (1994) show that factors such as asymmetric information across investors and differences of opinion would result in positively correlated order flows, and lagged order flows serve as proxies for these sources of trades. In addition, persistent factors, such as investors' sentiment about certain stocks or sectors, that are not captured by past returns could also induce serial correlations in order flow.

Factors other than the ones we include in the regression would also likely affect BUYS and SELLS. For example, if certain investors have private information about pending good news about a firm, then they would initiate buy trades,

[3] We report the results for regressions that use 3 lags on the dependent variables as a control, but in untabulated results we find that inclusion of 12 lags of dependent variables does not materially change the results.

leading to positive order imbalances. We do not include a proxy for such informed trading because such private information is unobservable by its very nature.[4] Nevertheless, as Proposition 1 shows, the relations predicted by various hypotheses will be obtained even in the presence of such additional factors because they have the same effect on decisions to buy or sell, and these decisions will affect both losers and winners.

Table 2 reports the time-series averages of the monthly slope coefficients and the t-statistics computed using Newey–West (1987) standard errors with 3 lags

TABLE 2

Cross-Sectional Determinants of BUYS and SELLS for NYSE Stocks

We run the following cross-sectional regression for each month:

$$Y_{i,t} \quad = \quad a_t + \sum_{j=1}^{12} b_{t,j} \mathrm{RET}_{i,t-j} + c_t \ln\left(\mathrm{SIZE}_{i,t-1}\right) + d_t \ln\left(\mathrm{BM}_{i,t-1}\right) + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{3} f_{t,j} Y_{i,t-j} + u_{i,t},$$

where Y is either BUYS, −SELLS, or BUYS − SELLS. We measure BUYS and SELLS in both number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., months $t-1$ to $t-12$). The slope coefficients for the BUYS − SELLS regressions are not the sum of the corresponding slope coefficients for the BUYS and −SELLS regressions because the independent variables include respective lagged dependent variables, which differ across the three specifications. Return (RET) is in percentage per month, SIZE is market capitalization in millions of dollars, BM is book-to-market ratio, and VOL is the standard deviation of returns in percentage per month calculated using daily returns within the month. The table reports the time-series averages of the coefficients (multiplied by 100) together with their Newey–West (1987) corrected t-statistics (using 3 lags) reported in parentheses. Panel B presents the joint economic significance of regression coefficients on lagged returns and lagged dependent variables. We first predict BUYS and SELLS for each month using the following prediction equations:

$$Y_{i,t}^{\mathrm{PREDICTED\_RETURNS}} \quad = \quad \bar{a} + \sum_{j=1}^{12} \bar{b}_j \mathrm{RET}_{i,t-j} \quad \text{and} \quad Y_{i,t}^{\mathrm{PREDICTED\_LAGS}} \quad = \quad \bar{a} + \sum_{j=1}^{3} \bar{f}_j Y_{i,t-j},$$

where the bars on top of the coefficients denote the average of the time-series coefficients from the previous regression. For each month, we rank stocks based on the predicted Ys and form deciles based on this ranking. We judge the economic significance of predictability based on each set of independent variables based on the differences between the Ys of the extreme deciles in the following month. The numbers reported in square brackets in Panel B are the differences divided by the corresponding standard deviations. The sample includes all NYSE stocks over the period 1993–2010.

	Number of Trades			Shares Traded		
	BUYS	−SELLS	BUYS − SELLS	BUYS	−SELLS	BUYS − SELLS
Panel A. Regression Coefficients						
Constant	29.36 (12.00)	−29.93 (−15.03)	0.29 (0.25)	31.73 (11.05)	−43.15 (−17.14)	−12.27 (−6.41)
RET(−1)	−3.61 (−1.59)	−10.73 (−7.16)	−10.70 (−6.04)	−11.23 (−6.02)	2.51 (1.31)	−3.71 (−4.55)
RET(−2)	1.73 (1.33)	−4.76 (−5.38)	−2.38 (−4.02)	−1.68(−1.44)	−1.14 (−0.97)	−2.00 (−3.17)
RET(−3)	5.56 (5.63)	−6.45 (−7.92)	−0.17 (−0.44)	4.27 (4.19)	−4.97 (−5.34)	−0.43 (−0.71)
RET(−4)	6.22 (6.26)	−5.45 (−7.00)	2.31 (4.45)	6.16 (5.26)	−5.67 (−5.11)	1.57 (2.94)
RET(−5)	5.09 (6.19)	−3.99 (−5.93)	2.37 (5.33)	6.18 (5.90)	−5.20 (−4.03)	1.86 (3.07)
RET(−6)	8.34 (7.94)	−6.73 (−8.19)	2.79 (5.77)	7.93 (7.26)	−6.51 (−6.67)	2.70 (4.30)
RET(−7)	4.69 (5.36)	−3.60 (−4.73)	2.32 (5.37)	4.37 (4.31)	−3.22 (−3.05)	2.41 (4.13)
RET(−8)	4.83 (5.81)	−4.34 (−5.71)	1.49 (4.25)	6.42 (6.44)	−6.24 (−6.15)	1.23 (2.63)
RET(−9)	3.97 (5.99)	−3.68 (−5.59)	1.24 (2.92)	5.84 (6.70)	−4.86 (−5.24)	1.84 (4.16)
RET(−10)	3.08 (3.65)	−2.75 (−3.48)	1.18 (3.03)	4.92 (4.42)	−5.29 (−4.88)	0.65 (1.62)
RET(−11)	1.81 (2.45)	−1.19 (−1.80)	1.36 (3.74)	2.25 (2.42)	−2.42 (−2.70)	0.60 (1.09)
RET(−12)	3.72 (4.87)	−2.58 (−3.82)	1.74 (4.75)	5.42 (5.62)	−4.39 (−4.14)	1.61 (3.26)
ln(SIZE(−1))	−0.30 (−1.82)	0.25 (1.81)	0.07 (1.11)	−0.03 (−0.15)	0.80 (5.06)	1.00 (7.92)
ln(BM(−1))	−0.65 (−3.88)	−0.06 (−0.56)	−0.71 (−7.07)	−0.40 (−2.56)	0.40 (2.30)	−0.04 (−0.59)
VOL(−1)	−28.60 (−9.68)	16.60 (7.40)	−3.91 (−2.55)	−8.90 (−2.78)	−0.85 (−0.27)	1.49 (0.94)
$Y(-1)$	0.50 (38.05)	0.44 (35.16)	0.32 (21.43)	0.34 (35.29)	0.29 (26.03)	0.17 (13.59)
$Y(-2)$	0.05 (5.66)	0.05 (7.06)	0.10 (10.62)	0.06 (11.50)	0.06 (11.70)	0.07 (8.60)
$Y(-3)$	0.06 (12.56)	0.06 (11.15)	0.09 (13.23)	0.06 (16.65)	0.05 (12.33)	0.08 (11.64)
Average adj. R^2	35.02	30.85	24.45	18.88	15.00	9.60
Average no. of stocks	1,304	1,304	1,304	1,304	1,304	1,304
Panel B. Economic Significance						
All return lags	0.180 [0.61]	0.174 [0.73]	0.036 [0.25]	0.103 [0.28]	0.087 [0.24]	0.022 [0.10]
All Y lags	0.528 [1.78]	0.387 [1.62]	0.023 [1.63]	0.473 [1.29]	0.395 [1.11]	0.191 [0.87]

[4]See Sarkar and Schwartz (2009) for an analysis of information-related motives of trading.

from the regression in equation (1). As we show in Proposition 1 of the model, the sign of the slope coefficients with BUYS as the dependent variable is determined by the relative number of contrarian and momentum traders. The buy decisions of disposition traders and tax-motivated traders are not influenced by past returns, and hence they do not play a role in the BUYS regression.

In the BUYS regression, the slope coefficients on the first 2 lagged returns are not significantly different from 0 during the full sample period for the regressions with number of trades, suggesting that neither momentum investors nor contrarian traders are dominant buyers. However, the slope coefficient on 1-month lagged return is significantly negative with number of shares traded. This is consistent with buying of losers and suggests that institutions (whose impact is more likely to manifest when examining shares traded as opposed to the number of trades) are contrarian at short horizons. The slope coefficients are all significantly positive when we consider horizons of 3 months or longer. The slope coefficients (t-statistics) range from 1.81 (2.45) on 11-month lagged returns to 8.34 (7.94) on 6-month lagged returns for the regression with number of trades. Therefore, buyer-initiated trades predominantly come from momentum traders who base their decisions on returns over horizons of 3 months and longer.

The slope coefficients on lagged returns are negative in −SELLS regressions. For instance, the coefficients in the −SELLS regressions with number of trades range from −1.19 to −10.73, and all but one of them are statistically significant. These results indicate that investors are more likely to initiate sell trades for winners than for losers.

Whereas the BUYS regression results suggest that the momentum trading hypothesis is relatively more important for buying decisions, the −SELLS regressions suggest exactly the opposite. The difference is likely attributable to the presence of disposition traders, as implied by the results in Proposition 1. Because the disposition effect only affects decisions to sell, the combined effect of contrarian traders and disposition-effect traders likely dominate that of momentum traders for sell decisions.

These findings illustrate the importance of using buy and sell trades separately in the empirical tests relative to using turnover. As Proposition 2 shows, all of these hypotheses make the same predictions for turnover, but in our tests, we can make sharper distinctions among them. Our overall results are inconsistent with any single hypothesis, and they indicate that multiple hypotheses are simultaneously necessary to explain investors' decisions to trade.

Table 2 also presents the results using BUYS − SELLS as the dependent variable. Proposition 1 states that the sign of the slope coefficient on the lagged returns depends on the presence of contrarian, disposition, and momentum traders. The regression with BUYS − SELLS as the dependent variable evaluates the net effect of various hypotheses that operate at different horizons. The slope coefficients on the first 3 lagged returns are negative (the first two coefficients are significantly negative), and the other coefficients on returns at longer lags are positive and significant. The negative slope coefficients decline in magnitude and significance with increasing lags. For example, with BUYS − SELLS measured in number of trades, the slope coefficients on the first 3 lagged returns decline (in absolute terms) from −10.70 to −0.17. Therefore, contrarian and disposition investors' trades based on short-horizon returns dominate those of momentum traders.

The slope coefficients are positive for returns at all longer lags, and almost all of them are statistically significant. We find similar results for regressions with both number of trades and with shares traded. Therefore, momentum trades based on returns at these horizons have a dominant effect. It is important to note that, consistent with Proposition 1, the difference in signs across the BUYS, −SELLS, and BUYS − SELLS regressions in Table 2 point to the importance of all three (contrarian, disposition, and momentum) types of traders.

There is a possibility that informed traders sell their winners when they reach their private target prices. It is difficult to distinguish such trades from those of disposition traders. However, informed traders are also likely to purchase undervalued shares after a price decline, but disposition traders will hold onto their depreciated shares. We do see some evidence of purchases of last-month losers, and this is consistent with both informed and contrarian trading.

A. Results in Perspective

Our findings regarding the relation between aggregate trades and past returns differ in many respects from the evidence in the literature for different subsets of investors. For example, Grinblatt et al. (1995) and others find evidence of momentum trading among institutions, and Gompers and Metrick (2001) report evidence of contrarian trading. Our results indicate that investors are largely momentum traders when they initiate buy trades but contrarians or disposition-based traders when they initiate sell trades. When we consider BUYS − SELLS, the aggregate market follows both momentum trading and contrarian or disposition-based trading, but at different horizons.

Our results also indicate that the findings of Statman et al. (2006) of a positive correlation between past returns and turnover are only partly attributable to the disposition effect. Although our evidence for SELLS is consistent with the disposition effect, we find that momentum trading is relatively more important for BUYS. In fact, at horizons longer than 3 months, the effect of past returns on buyer-initiated trades is stronger than that on seller-initiated trades, and we find a positive relation between past returns and net trades. Therefore, investors' tendency to follow a momentum trading strategy contributes more to the increase in turnover than does the disposition effect.

Hvidkjaer (2006) reports some results that are partially consistent with our results, although they are not directly comparable. Hvidkjaer examines the relation between order imbalances over a 6-month holding period for small and large trades and past 6-month returns. In contrast, we examine the relation between past monthly returns and aggregate BUYS, SELLS, and BUYS − SELLS each month.

Interestingly, the signs of the slope coefficients on lagged returns in the BUYS − SELLS regression in Table 2 are similar to the signs of the slope coefficients on lagged returns noted by Jegadeesh (1990), who uses returns as the dependent variable. Because correlation is not transitive, there is no mathematical reason why the pattern of relation between BUYS − SELLS and past returns should be the same as that between returns and past returns. In fact, in our later tests, we find that the signs of the slope coefficients when we regress BUYS − SELLS in

January against past returns are the opposite of those of the signs for the corresponding coefficients with returns that Jegadeesh reports (see Section IV.C), and we find similar differences when we consider past returns over longer horizons as well (see Section V.B).

Also, from an economic perspective, if these return patterns were a result of rational price formation, then order imbalance would be correlated with contemporaneous returns but not with lagged returns. Some behavioral motivations for trades suggest that the correlation between order imbalances and past returns would be positive, but others suggest a negative correlation. For example, explanations for momentum based on underreaction would suggest that there would be a positive correlation, but the overreaction and delayed-correction explanations predict a negative relation. Moreover, none of these explanations suggests that BUYS and SELLS would both be correlated in the same direction with past returns, as we find. Therefore, the relation between aggregate order flows and lagged returns can only be addressed empirically, which we do.

B. Economic Significance

This subsection evaluates the economic significance of the aggregate effects of the lagged returns and of aggregate lagged trades on buy, sell, and net trades. We follow the methodology of Jegadeesh (1990) to examine the economic significance of combined effects of subsets of these independent variables. We first predict BUYS and SELLS for each month using the following equations:

$$(2) \qquad \begin{aligned} Y_{i,t}^{\text{PREDICTED\_RETURNS}} &= \bar{a} + \sum_{j=1}^{12} \bar{b}_j \text{RET}_{i,t-j}, \\ Y_{i,t}^{\text{PREDICTED\_LAGS}} &= \bar{a} + \sum_{j=1}^{3} \bar{f}_j Y_{i,t-j}, \end{aligned}$$

where the bars on top of the coefficients denote the average of the time-series coefficients from the regression in equation (1). We use this approach to identify the contributions of each set of variables, keeping the other variables constant.

For each month, we rank stocks based on the predicted Ys and form deciles based on this ranking. We judge the economic significance of predictability based on each set of independent variables based on the differences between the Ys of the extreme deciles in the following month. For instance, the difference between the BUYS for deciles 10 and 1 based on the predicted value from equation (2) provides a measure of the economic significance of the predictability of buyer-initiated trades based on past returns.

Panel B of Table 2 presents differences in trades based on each of these predictive regressions. To put these differences in perspective, we divide the differences by the standard deviation of the corresponding trade measures and report the standardized values in square brackets. For returns-based predictions, the differences for the number of BUYS, SELLS, and net trades are 18%, 17%, and 4%, respectively. These differences divided by the corresponding standard deviations are 0.61, 0.73, and 0.25, respectively. Similar results are obtained for BUYS and SELLS measured in number of shares. Because past returns generally affect both buy and sell decisions in the same direction, their impact on net trades is smaller than that on BUYS and SELLS.

To examine the economic significance nonparametrically, we compute the percentage of months when the sign of the trade differences between the extreme deciles is in the same direction as that predicted by equation (2). For shares trades, the difference is of the predicted sign in 90%, 87%, and 77% of the months for BUYS, −SELLS, and BUYS − SELLS, respectively, and the corresponding frequencies are bigger for number of trades. Overall, these results indicate that past returns have a nontrivial impact on investors' trading decisions.

Given their persistence, the lagged dependent variables are strong predictors as well. The standardized differences between decile 10 and decile 1 stocks for shares bought, shares sold, and net shares traded are 1.29, 1.11, and 0.87, respectively. The signs of the trade differences between the extreme deciles are almost always in the same direction as predicted by equation (2) in all specifications. Thus, the impact of the lagged dependent variables on trading decisions is even stronger than that of past returns.

We also examine the impact of each of the individual characteristics in the regression in equation (1) on trades. Because we consider each characteristic individually, we measure the impact of the characteristic as the product of the corresponding coefficient in Table 2 and the average of the characteristics for the extreme decile portfolios. The differences between the average characteristics of the extreme decile portfolios are 6.1, 3.0, and 0.24 for ln(SIZE), ln(BM), and VOL, respectively. The impact is mostly marginal (0.01 and 0.07 times the standard deviation) when we consider number of shares traded, except for size, where the ratio is 0.28 times the standard deviation for BUYS − SELLS. We find a somewhat bigger impact of volatility at −0.23 and 0.17 times the standard deviation for BUYS and SELLS in terms of number of trades and −0.15 for BUYS − SELLS with book-to-market. The impacts in the other cases are marginal.

C. Tax-Loss Selling

The seasonal tax-loss selling hypothesis predicts that investors are more likely to sell losers than winners in December and more likely to sell winners in January to defer realization of capital gains by a year. The literature also hypothesizes that the tax-loss selling hypothesis can explain the evidence that past losers earn positive abnormal returns in January and that small firms outperform large firms in January (the January effect). For example, Reinganum (1983) and others[5] argue that intense tax-loss selling for losers depresses their stock prices in December; however, they earn abnormal returns when they rebound the following January.

Constantinides (1984) and Chan (1986) question the idea that tax-loss selling in December would result in any price pressure. These authors note that although the wash-sale provision in the tax code would deter the tax-loss sellers from buying back the stock they sold within a 30-day window, they can buy losers that others have sold. In effect, this hypothesis implies that any price pressure attributable to tax-loss selling should be offset by buying pressure from other investors, and

[5]See, for instance, Jones, Pearce, and Wilson (1987), Roll (1983), Reinganum and Shapiro (1987), and Poterba and Weisbenner (2001).

hence tax-loss selling cannot be a plausible explanation for the January effect. The offsetting buying-pressure hypothesis implies that the increased December turnover for losers that Lakonishok and Smidt (1986) document is driven not only by investors' decisions to sell losers but also by incentives to buy these losers to take advantage of any price pressure. Constantinides (1984) and Chan (1986) argue that because of the offsetting incentives to buy, tax-loss selling would not result in depressed prices for losers in December and abnormal returns in January.

Is there buying pressure in December that at least partially offsets tax-loss selling in December, or does the increased turnover for losers in December come only from seller-initiated trades? We address this question directly by examining the relation between past returns and BUYS and SELLS separately. We examine the turn-of-the-year effect using the following regression:

$$(3) \qquad \hat{b}_{t,j} \quad = \quad b_{0,j} + b_{\mathrm{DEC},j} I_t\,(\mathrm{DEC}) + b_{\mathrm{JAN},j} I_t\,(\mathrm{JAN}),$$

where $\hat{b}_{t,j}$ is the estimated slope coefficient on lagged return at lag j in month t from equation (1), and $I(\mathrm{DEC})$ and $I(\mathrm{JAN})$ are the dummy variables for December and January, respectively. The slope coefficients $b_{\mathrm{DEC},j}$ and $b_{\mathrm{JAN},j}$ are the differences between the slope coefficients in December and January from the averages in other months. Our approach fits the regression in equation (3) as the second step using the monthly estimates of the regression in equation (1), but this approach can also be viewed as a panel-regression version of equation (1) with pooled cross-sectional and time-series observations that also includes dummies for December and January interacted with past returns as additional independent variables.

Table 3 presents the Dec. and Jan. slope coefficients, which equal the difference between the return coefficients in these months and in other calendar months. For −SELLS, the December slope coefficients are positive and mostly significant. The first seven January slope coefficients are negative and mostly significant. These results indicate that investors are more likely to sell losers in December and winners in January than in other months, which is consistent with the tax-loss selling hypothesis. F-statistics reject the null hypothesis that the slope coefficients are jointly equal to 0 for −SELLS in both the December and January regressions.

For BUYS, the December slope coefficients are all negative and mostly significant. These results indicate that investors are also more likely to buy losers in December than in other months. Therefore, consistent with the predictions of Constantinides (1984) and Chan (1986), losers also experience increased buyer-initiated trades.

Does this buying pressure fully offset the tax-loss selling pressure? For net trades (BUYS − SELLS), the December slope coefficients are all positive for number of trades and jointly significantly different from 0. The slope coefficients are all positive in the shares regression as well. However, the F-statistic of 1.50 that tests the hypothesis that these coefficients are jointly equal to 0 is not significant at the 5% level. Therefore, the increased selling pressure for losers is at least partially offset by buyer-initiated trades, consistent with the arguments of Constantinides (1984). Thus, our evidence indicates that the increased selling pressure for losers does not necessarily imply price pressure and provides some

TABLE 3
Tax-Loss Selling in NYSE Stocks

We run the following cross-sectional regression for each month:

$$Y_{i,t} = a_t + \sum_{j=1}^{12} b_{t,j}\mathrm{RET}_{i,t-j} + c_t \ln\left(\mathrm{SIZE}_{i,t-1}\right) + d_t \ln\left(\mathrm{BM}_{i,t-1}\right) + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{3} f_{t,j} Y_{i,t-j} + u_{i,t},$$

where Y is either BUYS, −SELLS, or BUYS − SELLS. We measure BUYS and SELLS in both number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., months $t-1$ to $t-12$). Return (RET) is in percentage per month, SIZE is market capitalization in millions of dollars, BM is book-to-market ratio, and VOL is the standard deviation of returns in percentage per month calculated using daily returns within the month. We then run a second-stage regression on the time series of $b_{t,j}$ coefficients as follows:

$$\hat{b}_{t,j} = b_{0,j} + b_{\mathrm{DEC},j} I_t\,(\mathrm{DEC}) + b_{\mathrm{JAN},j} I_t\,(\mathrm{JAN}),$$

where the indicator variables are 1 if the corresponding month is December or January, and 0 otherwise. Panel A presents the dummy coefficients b_{DEC} and b_{JAN} together with their Newey–West (1987) corrected t-statistics (using 3 lags) reported in parentheses. The F-statistics are computed under the hypothesis that the slope coefficients on the dummy variables are jointly equal to 0. The 95% critical value for the F-statistics is 1.80. Panel B presents the economic significance of these coefficients. This is calculated as the product of the sum of the corresponding dummy coefficients and the monthly excess return on winners (6.96%) and losers (−4.43%) in excess of the market return. Winners and losers are defined as the ones in the 95th and 5th percentiles of the 12-month return cross-sectional distribution. The sample includes all NYSE stocks over the period 1993–2010.

	Number of Trades			Shares Traded		
	BUYS	−SELLS	BUYS − SELLS	BUYS	−SELLS	BUYS − SELLS
Panel A. Dummy Coefficients						
RET(−1) × DEC	−9.55 (−2.07)	19.62 (4.67)	9.01 (3.92)	−13.15 (−2.80)	22.33 (4.13)	7.88 (3.64)
RET(−2) × DEC	−3.44 (−1.46)	9.84 (3.30)	5.59 (3.08)	−4.43 (−2.41)	7.03 (2.30)	2.27 (1.12)
RET(−3) × DEC	−7.42 (−3.44)	10.43 (3.92)	3.90 (2.30)	−7.80 (−2.33)	9.68 (2.99)	1.97 (0.65)
RET(−4) × DEC	−5.51 (−1.61)	8.93 (3.29)	3.79 (1.79)	−5.48 (−1.77)	8.67 (2.68)	2.52 (1.00)
RET(−5) × DEC	−5.11 (−2.20)	6.51 (2.43)	2.09 (1.30)	−1.99 (−0.74)	4.12 (1.38)	2.64 (1.05)
RET(−6) × DEC	−2.06 (−0.76)	7.36 (2.43)	5.88 (2.97)	0.62 (0.20)	3.36 (1.09)	4.22 (2.62)
RET(−7) × DEC	−5.99 (−2.32)	9.44 (4.73)	3.41 (1.84)	−6.11 (−1.74)	9.35 (4.00)	2.29 (1.14)
RET(−8) × DEC	−4.44 (−2.25)	9.20 (5.08)	4.26 (3.02)	−6.95 (−2.91)	8.71 (3.75)	0.97 (0.65)
RET(−9) × DEC	−3.97 (−2.34)	8.93 (4.20)	4.57 (2.28)	−7.45 (−4.02)	11.67 (4.64)	3.63 (2.36)
RET(−10) × DEC	−1.71 (−0.95)	7.68 (3.85)	5.32 (2.75)	−2.34 (−0.89)	5.33 (1.83)	2.44 (1.39)
RET(−11) × DEC	−5.68 (−2.58)	6.40 (2.80)	0.05 (0.05)	−5.80 (−1.97)	7.25 (3.12)	0.86 (0.41)
RET(−12) × DEC	−5.32 (−2.51)	9.57 (3.32)	3.76 (2.28)	−9.24 (−2.97)	11.70 (3.37)	2.47 (1.01)
F-statistic	3.39	3.96	3.58	5.23	6.80	1.50
RET(−1) × JAN	−0.44 (−0.10)	−8.40 (−2.41)	−7.04 (−1.60)	2.80 (0.71)	−7.33 (−2.01)	−7.08(−2.23)
RET(−2) × JAN	5.79 (1.21)	−11.30 (−3.07)	−5.69 (−2.28)	9.78 (2.17)	−8.15 (−1.80)	1.92 (0.89)
RET(−3) × JAN	4.84 (1.66)	−10.09 (−3.69)	−4.24 (−3.46)	5.94 (1.51)	−7.60 (−2.17)	−3.44 (−1.45)
RET(−4) × JAN	6.79 (1.36)	−9.40 (−2.67)	−2.47 (−1.09)	9.79 (2.24)	−12.31 (−3.38)	−3.57 (−1.39)
RET(−5) × JAN	3.95 (1.73)	−7.87 (−3.65)	−3.58 (−2.60)	4.62 (1.77)	−3.92 (−1.26)	−0.29 (−0.13)
RET(−6) × JAN	4.25 (1.60)	−5.13 (−1.96)	0.22 (0.18)	2.30 (0.83)	−4.56 (−1.64)	−2.93 (−1.65)
RET(−7) × JAN	6.83 (1.50)	−8.95 (−2.24)	−1.23 (−0.91)	6.96 (1.45)	−9.98 (−2.24)	−3.45 (−2.03)
RET(−8) × JAN	−2.38 (−0.88)	−1.11 (−0.52)	−4.13 (−3.31)	−2.83 (−1.03)	3.89 (1.29)	0.10 (0.06)
RET(−9) × JAN	0.95 (0.41)	−2.51 (−1.40)	−1.54 (−1.60)	1.35 (0.49)	−0.96 (−0.43)	−0.01 (−0.00)
RET(−10) × JAN	−2.49 (−1.12)	0.18 (0.08)	−1.30 (−1.17)	−2.42 (−0.91)	3.23 (1.13)	0.32 (0.26)
RET(−11) × JAN	−0.49 (−0.20)	0.00 (0.00)	−0.04 (−0.04)	−3.78 (−1.15)	6.02 (2.30)	2.25 (1.09)
RET(−12) × JAN	−1.38 (−0.63)	1.83 (1.08)	−0.35 (−0.28)	−1.74 (−0.64)	3.81 (1.41)	2.09 (1.45)
F-statistic	2.17	2.95	2.66	2.97	2.77	2.76
Panel B. Economic Significance						
Winners, DEC	−0.042	0.079	0.036	−0.049	0.076	0.024
Losers, DEC	0.027	−0.051	−0.023	0.031	−0.048	−0.015
Winners, JAN	0.018	−0.044	−0.022	0.023	−0.026	−0.010
Losers, JAN	−0.012	0.028	0.014	−0.015	0.017	0.006

support for the arguments of Brown, Keim, Kleidon, and Marsh (1983) and Chan (1986) that tax-loss selling may not be the explanation for the January effect.

The January slope coefficients for BUYS are generally positive but, with a few exceptions, not significant.[6] This evidence indicates that investors are no

[6]When we fit the regression in equation (1) for only BUYS − SELLS in January, we find that the slope coefficients on lagged returns are mostly positive. These results are different from those of Jegadeesh (1990) (who uses January returns as the dependent variable).

more likely to buy past losers or past winners in January than in other months. Therefore, unlike in December, increased seller-initiated trades for past winners in January do not attract additional buyer-initiated trades.

To understand the economic significance of the turn-of-the-year slope coefficients, we compute the incremental trades for winners and losers in the months of January relative to other months. We define loser and winner stocks as ones in the 5th and 95th percentiles of the 12-month returns distribution. We choose these percentiles because they are the median returns for stocks in the loser and winner deciles.

The 5th and 95th percentiles of the average 12-month returns minus the market returns are −55.2% and 81.5%, respectively. Therefore, the expected returns in each of the previous 12 months for the winners and losers are −4.43% and 6.96%, respectively. The difference between trades around the turn of the year and in other months for winners and losers, keeping their returns fixed, is the sum of the product of these returns with the corresponding lagged return coefficients.

Panel B of Table 3 presents the turn-of-the-year difference in trades for winners and losers. For the month of December, losers experience an increase of 5.1% in SELLS and 2.7% in BUYS. The net SELLS increases by 2.3%. The SELLS for winners decrease by 7.9%, as expected. The magnitude of decline in seller-initiated trades for winners is, in fact, larger than the magnitude of increase in that for losers.

BUYS for winners also declines in December, which is the opposite of what we find for losers. This result indicates that when there is a lack of seller-initiated trades, buyer-initiated trades also dry up. These results also indicate that the increase in December turnover for losers relative to winners that Lakonishok and Smidt (1986) find is as much attributable to an increase in the turnover for losers as it is to a decrease in turnover for winners.

The SELLS for losers decline by 2.8% in January, and those for winners increase by 4.4%. The BUYS for winners increase by 1.8% in January. In our nonparametric test, the differences between the BUYS and SELLS of the extreme deciles were in the same direction as predicted in all Januarys. BUYS − SELLS differences between the extreme deciles were of the predicted signs in 63% of Januarys, which is also statistically significant. These results provide new insights into how a tax-related incentive or disincentive for selling stocks results in an indirect incentive for buying stocks as well. Therefore, although the tax-loss selling hypothesis is directly related only to seller-initiated trades, it affects buyer-initiated trades as well.

The 1986 Tax Reform Act (TRA) set Oct. 31 as the tax year-end for mutual funds. Therefore, the seasonal tax-motivated trades of these institutions may be concentrated in October and November. However, we do not find any seasonal trading patterns in October and November.[7]

[7]Gibson, Safieddine, and Titman (2000) examine mutual fund trades following the passage of TRA and find a strong "November effect" in the first year after the passage but do not find any effect in the subsequent years.

V. Additional Tests

A. Pre-1997 NASDAQ Data

It is possible that some trade initiators use limit orders to execute their trades. These trade initiators may trade against other trade initiators, but we will not be able to identify algorithmically that active traders were involved on both sides of such trades. Although such crossing trades are not uncommon today, in the pre-1997 period, market makers were typically on the passive side of each trade on the NASDAQ market. Therefore, we can more accurately identify the trade initiator in the pre-1997 NASDAQ data and test the robustness of our findings.

We obtain NASDAQ trade and quote data from two sources. Data for the 1993–1996 period are from TAQ, and data for the 1987–1992 period are from the Institute for the Study of Security Markets (ISSM). Table 4 presents the results of the regression in equation (1) estimated on pre-1997 NASDAQ data. The results for BUYS − SELLS are quite similar to those in Table 2. For example, the slope coefficients on the first 3 lagged returns are negative (most of them statistically significantly so) in both samples, and the coefficients at longer lags are all positive (although many of them are not statistically significant in the regression with shares traded). Thus, as with the full NYSE sample, contrarian and/or disposition trading dominate at shorter horizons, whereas momentum trading dominates at the longer horizons for the NASDAQ sample of stocks.

There are some differences in the results between the NYSE sample and the NASDAQ sample. One difference between the results in Table 2 and Table 4 is the magnitude of the coefficients on the lagged returns for separate BUYS and SELLS regressions; the estimated coefficients in Table 4 are far larger. For instance, the coefficient on the first lag of returns for the −SELLS in the number-of-trades regression in Table 4 is −43.61 as compared with −10.70 in Table 2. This difference in the magnitude of the slope coefficients is likely attributable to the fact that we can more accurately classify buyer- and seller-initiated trades in the NASDAQ sample. Another difference is the lack of short-term contrarian buying in the NASDAQ sample. The first-lag return coefficients for the −SELLS regression for shares and trades are both negative in Table 4 (the coefficient for the −SELLS regression with shares traded was positive, although insignificant, in Table 2), and this is consistent with both contrarian selling of winners and the disposition effect. Yet, another difference is the change in signs at lags 11 and 12 in the BUYS and −SELLS regressions, although only the coefficients on RET(−11) and RET(−12) are significant at the 5% level in the −SELLS regressions for trades, suggesting that at lags 11 and 12, there is selling of losers by the momentum traders. Apart from these differences, there is overall evidence of momentum trading as well as the contrarian/disposition effect in the NASDAQ sample. Moreover, as in the NYSE sample, the momentum effect is stronger and dominates at longer lags, whereas the contrarian/disposition effect dominates at shorter lags.

B. Effect of Returns at Longer Lags

The results in Table 2 indicate that even 12-month lagged returns affect order imbalances. This subsection examines the effect of returns at longer lags as well, using the following regression:

$$(4) \quad Y_{i,t} = a_t + b_{t,1}\mathrm{RET}_{i,t-1:t-3} + b_{t,2}\mathrm{RET}_{i,t-4:t-12} + b_{t,3}\mathrm{RET}_{i,t-13:t-36} + b_{t,4}\mathrm{RET}_{i,t-37:t-60} + c_t \ln(\mathrm{SIZE}_{i,t-1}) + d_t \ln(\mathrm{BM}_{i,t-1}) + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{60} f_{t,j} Y_{i,t-j} + u_{i,t}.$$

TABLE 4

Cross-Sectional Determinants of BUYS and SELLS for NASDAQ Stocks

We run the following cross-sectional regression for each month:

$$Y_{i,t} = a_t + \sum_{j=1}^{12} b_{t,j}\mathrm{RET}_{i,t-j} + c_t \ln(\mathrm{SIZE}_{i,t-1}) + d_t \ln(\mathrm{BM}_{i,t-1}) + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{3} f_{t,j} Y_{i,t-j} + u_{i,t},$$

where Y is either BUYS, −SELLS, or BUYS − SELLS. We measure BUYS and SELLS in both number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., months $t-1$ to $t-12$). The slope coefficients for the BUYS − SELLS regressions are not the sum of the corresponding slope coefficients for the BUYS and −SELLS regressions because the independent variables include respective lagged dependent variables, which differ across the three specifications. Return (RET) is in percentage per month, SIZE is market capitalization in millions of dollars, BM is book-to-market ratio, and VOL is the standard deviation of returns in percentage per month calculated using daily returns within the month. The table reports the time-series averages of the coefficients (multiplied by 100) together with their Newey–West (1987) corrected t-statistics (using 3 lags) reported in parentheses. Panel B shows the joint economic significance of the regression coefficients on lagged returns and lagged dependent variables. We first predict BUYS and SELLS for each month using the following prediction equations:

$$Y_{i,t}^{\mathrm{PREDICTED\_RETURNS}} = \bar{a} + \sum_{j=1}^{12} \bar{b}_j \mathrm{RET}_{i,t-j} \quad \text{and} \quad Y_{i,t}^{\mathrm{PREDICTED\_LAGS}} = \bar{a} + \sum_{j=1}^{3} \bar{f}_j Y_{i,t-j},$$

where the bars on top of the coefficients denote the average of the time-series coefficients from the previous regression. For each month, we rank stocks based on the predicted Ys and form deciles based on this ranking. We judge the economic significance of predictability based on each set of independent variables based on the differences between the Ys of the extreme deciles in the following month. The numbers reported in square brackets in Panel B are differences scaled by corresponding standard deviations. The sample includes all NASDAQ stocks over the period 1987–1996.

	Number of Trades			Shares Traded		
	BUYS	−SELLS	BUYS − SELLS	BUYS	−SELLS	BUYS − SELLS
Panel A. Regression Coefficients						
Constant	40.71 (5.89)	−54.78 (−10.18)	−12.97 (−5.65)	31.20 (5.11)	−61.69 (−9.77)	−33.37 (−10.63)
RET(−1)	23.11 (5.04)	−43.61 (−15.14)	−15.34 (−7.30)	21.37 (7.89)	−32.36 (−14.02)	−4.83 (−3.00)
RET(−2)	11.03 (5.40)	−18.76 (−13.63)	−4.45 (−5.05)	12.72 (7.37)	−19.14 (−9.41)	−2.92 (−2.21)
RET(−3)	9.71 (5.82)	−13.55 (−9.99)	−1.78 (−3.06)	12.37 (8.48)	−15.06 (−10.88)	−0.51 (−0.50)
RET(−4)	9.63 (6.49)	−10.33 (−8.14)	1.63 (3.09)	10.91 (7.48)	−12.23 (−6.98)	0.19 (0.17)
RET(−5)	9.44 (6.04)	−8.55 (−6.57)	2.67 (4.18)	9.85 (7.69)	−10.61 (−6.56)	0.22 (0.20)
RET(−6)	7.24 (5.00)	−6.72 (−6.51)	2.19 (3.26)	8.37 (5.86)	−7.65 (−5.21)	1.77 (1.96)
RET(−7)	6.38 (5.49)	−5.59 (−5.19)	1.98 (2.65)	7.92 (5.95)	−4.96 (−3.05)	3.80 (3.16)
RET(−8)	6.22 (3.85)	−3.99 (−3.19)	3.24 (4.30)	6.99 (3.59)	−5.63 (−3.34)	2.25 (1.27)
RET(−9)	3.75 (3.12)	−1.51 (−1.54)	2.80 (4.09)	4.76 (3.92)	−2.13 (−1.52)	3.07 (2.32)
RET(−10)	0.56 (0.47)	1.32 (1.31)	2.47 (3.65)	0.81 (0.57)	−0.76 (−0.52)	0.63 (0.47)
RET(−11)	−0.94 (−0.72)	2.85 (2.75)	2.28 (3.61)	−0.27 (−0.18)	1.33 (0.82)	1.09 (1.10)
RET(−12)	−1.20 (−0.89)	3.75 (3.04)	2.73 (4.10)	−2.37 (−1.41)	3.73 (1.93)	1.70 (1.24)
ln(SIZE(−1))	−0.82 (−1.67)	1.58 (4.19)	0.92 (5.67)	0.35 (0.77)	1.20 (2.41)	1.87 (8.55)
ln(BM(−1))	−2.68 (−5.02)	0.86 (2.04)	−1.78 (−7.62)	−2.28 (−5.14)	1.59 (3.21)	−0.74 (−1.73)
VOL(−1)	−6.81 (−2.29)	9.93 (4.59)	5.94 (3.46)	7.68 (2.76)	−0.92 (−0.39)	10.26 (5.89)
$Y(-1)$	32.57 (9.58)	26.95 (10.07)	26.06 (16.16)	18.84 (10.06)	15.46 (9.53)	7.63 (11.37)
$Y(-2)$	7.47 (10.77)	6.95 (13.78)	8.88 (9.91)	5.60 (11.20)	4.75 (9.27)	4.06 (6.74)
$Y(-3)$	5.21 (6.80)	4.51 (7.91)	6.77 (8.69)	3.94 (5.12)	3.09 (3.94)	3.89 (4.36)
Average adj. R^2	16.69	16.65	14.06	7.31	5.20	1.44
Average no. of stocks	1,819	1,819	1,819	1,819	1,819	1,819
Panel B. Economic Significance						
All return lags	0.514 [0.69]	0.469 [0.86]	0.036 [0.09]	0.377 [0.48]	0.348 [0.39]	0.030 [0.04]
All Y lags	0.820 [1.10]	0.591 [1.09]	0.414 [1.02]	0.628 [0.80]	0.573 [0.64]	0.228 [0.33]

We compound returns over different horizons as independent variables (the return variables with two time subscripts denote the ending and starting points of the compounding period). We also include 60 lags of the dependent variable as controls.[8]

Table 5 presents the regression estimates. The slope coefficients on the first 3 lagged returns and on $\mathrm{RET}_{t-4:t-12}$ are consistent with the results in Table 2. The slope coefficients on $\mathrm{RET}_{t-13:t-24}$ and $\mathrm{RET}_{t-25:t-36}$ are an order of magnitude smaller than the coefficients on returns at shorter lags, although a few of them are statistically significant.[9] These results indicate that returns at lags longer than 1 year do not significantly affect order flows.

TABLE 5

Cross-Sectional Determinants of BUYS and SELLS for NYSE Stocks: Effect of Returns at Longer Lags

We run the following cross-sectional regression for each month:

$$\begin{aligned} Y_{i,t} \quad = \quad & a_t + b_{t,1}\mathrm{RET}_{i,t-1:t-3} + b_{t,2}\mathrm{RET}_{i,t-4:t-12} + b_{t,3}\mathrm{RET}_{i,t-13:t-36} + b_{t,4}\mathrm{RET}_{i,t-37:t-60} \\ & + c_t \ln\left(\mathrm{SIZE}_{i,t-1}\right) + d_t \ln\left(\mathrm{BM}_{i,t-1}\right) + e_t \mathrm{VOL}_{i,t-1} + \sum_{j=1}^{60} f_{t,j} Y_{i,t-j} + u_{i,t}, \end{aligned}$$

where Y is either BUYS, −SELLS, or BUYS − SELLS. We measure BUYS and SELLS in both number of trades and number of shares. We scale these variables by the average number of trades/trading volume over the previous 12 months (i.e., months $t-1$ to $t-12$). The slope coefficients for the BUYS − SELLS regressions are not the sum of the corresponding slope coefficients for the BUYS and −SELLS regressions because the independent variables include respective lagged dependent variables, which differ across the three specifications. Return (RET) is in percentage per month, SIZE is market capitalization in millions of dollars, BM is book-to-market ratio, and VOL is the standard deviation of returns in percentage per month calculated using daily returns within the month. The table reports the time-series averages of the coefficients (multiplied by 100) together with their Newey–West (1987) corrected t-statistics (using 60 lags) reported in parentheses. Coefficients greater than 1 on lags of the dependent variable are not shown for simplicity. The sample includes all NYSE stocks over the period 1993–2010.

	Number of Trades			Shares Traded		
	BUYS	−SELLS	BUYS − SELLS	BUYS	−SELLS	BUYS − SELLS
Constant	33.77 (8.01)	−34.82 (−7.03)	3.37 (1.79)	39.20 (9.54)	−48.69 (−6.82)	−1.42 (−0.61)
RET(−1: −3)	5.06 (3.02)	−7.93 (−6.10)	−0.95 (−1.47)	−0.11 (−0.10)	−2.66 (−2.31)	−1.59 (−2.98)
RET(−4: −12)	3.85 (6.04)	−3.87 (−6.35)	0.79 (2.18)	4.54 (5.69)	−3.72 (−5.31)	0.80 (3.19)
RET(−13: −36)	0.26 (2.64)	−0.22 (−2.49)	0.05 (1.38)	0.60 (3.96)	−0.42 (−3.28)	−0.04 (−0.44)
RET(−37: −60)	0.09 (0.63)	−0.05 (−0.51)	−0.02 (−0.62)	0.27 (1.22)	−0.12 (−0.61)	0.08 (2.81)
ln(SIZE(−1))	−0.14 (−0.49)	−0.02 (−0.07)	−0.10 (−1.19)	−0.09 (−0.44)	0.67 (1.97)	0.22 (1.19)
ln(BM(−1))	−0.25 (−0.93)	−0.07 (−0.28)	−0.13 (−3.15)	−0.02 (−0.05)	0.12 (0.28)	0.13 (1.80)
VOL(−1)	−27.48 (−5.39)	16.99 (5.46)	−6.00 (−4.58)	−10.18 (−5.83)	4.50 (2.17)	−2.51 (−2.46)
$Y(-1)$	0.51 (49.04)	0.48 (97.33)	0.29 (6.71)	0.36 (22.93)	0.33 (13.20)	0.16 (5.43)
$Y(-2)$ to $Y(-60)$			Not reported for brevity			
Average adj. R^2	42.69	40.44	29.24	24.71	22.15	19.14
Average no. of stocks	880	880	880	880	880	880

C. Robustness Tests

We also fit the regression in equation (1) separately for stocks in the Standard & Poor's (S&P) 500 Index and the rest of the stocks. Stocks in the index are larger and more actively traded than the other stocks. The signs of the slope coefficients and the overall results are similar to the results in Table 2 for both stocks in the index and nonindex stocks. The only difference is the level of significance of

[8]The results are similar if we use only 3 lags of dependent variables.

[9]The correlation between BUYS − SELLS and long-horizon returns (at lags of 2–5 years) is positive, but the literature on long-horizon return reversal suggests that the correlation is negative for returns.

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1-month lagged return coefficients.[10] We also find results similar to those in Table 2 when we partition the sample based on the previous month's median market capitalization. Therefore, our conclusions are similar for large and liquid stocks and for small stocks.

We also examine the results for subperiods demarcated by decimalization from 1993 to 2001 and from 2002 to 2010. We also consider the crisis period separately by breaking up the second subperiod into the periods from Jan. 2002 to June 2007 and July 2007 to Dec. 2010. The results are qualitatively similar in all of these subperiods.

VI. Conclusions

We examine the relation between order imbalances and past returns and test a number of hypotheses about motivations for trading that the literature proposes. Theoretical models of trading typically make predictions about whether buyers or sellers would initiate trades under various circumstances. We test these models using aggregate BUYS, SELLS, and net orders.

We find that both buyer- and seller-initiated trades increase with past returns. The difference between buyer- and seller-initiated trades is negatively related to short-horizon returns but positively related to returns over longer horizons up to a year. The results for buyer-initiated trades generally support the momentum trading hypothesis, but the results for seller-initiated trades provide support for the disposition effect and contrarian trading. We also find that investors are more likely to sell losers in December, which is consistent with the evidence in the literature. In addition, we find that losers also attract additional buyer-initiated trades in December, which would at least partially offset any price pressure attributable to tax-loss selling, as Constantinides (1984) predicts. Overall, our results indicate that the relative impacts of the hypotheses we examine are different for BUYS and SELLS, they vary over return horizons, and no single hypothesis can fully explain the pattern of relations between investors' trading decisions and past returns that we find.

In addition to past returns, we find that market capitalization, book-to-market ratio, and past order imbalances are useful in predicting future order imbalances. Our empirical model can help in identifying the expected and unexpected components of order flow, and future work can examine how these components are related to market impact and price discovery. Investors can potentially use the predictable pattern of order flow that we document to develop efficient trade execution strategies.

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