How Wise Are Crowds?

Insights from Retail Orders and Stock Returns

November 2010

Eric K. Kelley and Paul C. Tetlock*

University of Arizona and Columbia University

Abstract

We study the role of retail investors in stock pricing using uniquely extensive data on retail trades and firm newswires. We show that daily buy-sell imbalances in retail orders positively predict firms' returns at horizons up to 20 days and that predictability does not reverse at 60-day horizons. These return predictability findings apply to aggressive (market) and passive (limit) order types. Textual analysis of the newswires reveals that market order imbalances also predict the tone of news stories, but limit order imbalances do not. In contrast, limit orders benefit from daily return reversals, whereas market orders do not. Collectively, these findings suggest that retail market orders aggregate private information about firms' future cash flows, whereas retail limit orders provide liquidity to traders demanding immediate execution.

---

* Kelley and Tetlock appreciate research support from Arizona and Columbia, respectively. We thank the following people for their helpful comments: Brad Barber, Robert Battalio, Ekkehart Boehmer, Kent Daniel, Paul Irvine, Charles Jones, Tim Loughran, Terrance Odean, Christopher Parsons, Tano Santos, and Sheridan Titman, along with seminar participants at Alberta, Arizona, Columbia, DePaul, Emory, LBS, and LSE. We thank Travis Box for research assistance. All results and interpretations are the authors' and are not endorsed by our retail order data provider. Please send correspondence to paul.tetlock@columbia.edu.

There is intriguing recent evidence that retail order flow positively predicts firms' stock returns at horizons up to one month (Dorn, Huberman, and Sengmueller (2008), Kaniel, Saar, and Titman (2008) (hereafter KST), and Barber, Odean, and Zhu (2009) (hereafter BOZ)). To date, the search for an explanation has produced three leading theories with very different implications for the role of retail investors in stock pricing. The "private information" hypothesis is that retail flow positively predicts returns because some retail investors are well-informed about firms' future cash flows (Kaniel, Liu, Saar, and Titman (2008) (hereafter KLST)). The "liquidity provision" hypothesis is that retail investors earn a premium by taking the other side of institutional trades that exert temporary pressure on prices (KST). The "autocorrelated flow" hypothesis is the mechanical idea that current retail buying predicts more retail buying in the future, which leads to high future returns (Dorn, Huberman, and Sengmueller (2008) and BOZ). While the first two explanations suggest retail investors contribute to efficient stock pricing, the third implies the opposite.

We evaluate these non-exclusive explanations using trading and news data uniquely suited for this purpose. Our trading data source is retail order flow routed to two large market centers from 2003 to 2007. It includes 225 million executed trades and $2.6 trillion in volume, constituting the largest United States (US) database of retail orders ever studied.[1] Moreover, the data allow us to separately examine return predictability from market orders, nonmarketable limit orders, and executed limit orders. The identification of market orders is important for testing the autocorrelated flow hypotheses because market orders may exert more pressure on prices. Identifying limit orders is helpful in tests of the liquidity provision theory because patient retail traders may use limit orders to meet institutional demands for immediate execution.

[1] Only the Taiwanese retail order database studied in Barber, Lee, Liu, and Odean (2009) is larger.

We combine our retail order data with comprehensive newswire data from Dow Jones (DJ) to test the private information hypothesis. We assess whether net retail buying in each order type correctly predicts the linguistic tone of firm-specific news articles. The tone of news is a proxy for changes in firms' fundamental values, which we validate as discussed below.

Our three main findings offer new insights into the role of retail orders in stock pricing. First, daily buy-sell imbalances from both retail market orders and retail limit orders positively predict the cross-section of stock returns at horizons up to 20 days. Positive return predictability shows no sign of reversal and sometimes even persists at horizons up to 60 days. The lack of a reversal is inconsistent with a key prediction from the autocorrelated flow hypothesis.[2] Moreover, we find only weak evidence that return predictability is greater in stocks with more persistent order flow, casting further doubt on this hypothesis.

Second, market order imbalances correctly predict the tone of firm-specific news stories, whereas limit order imbalances do not. Both results hold at daily, weekly, and monthly horizons; and they are confirmed in further tests using earnings surprises as the proxy for changes in fundamentals. The finding for market orders is consistent with the information hypothesis. The finding for limit orders, however, is not consistent, leaving only the liquidity provision theory as a viable explanation.

Third, daily and intraday returns positively predict market order imbalances but negatively predict nonmarketable limit order imbalances. That is, market orders exhibit daily return momentum, whereas limit orders are contrary to daily returns. This is consistent with limit orders providing liquidity but casts doubt on this interpretation for market orders. Furthermore, we find that return predictability from limit orders is particularly strong in stocks with high bid-

[2] The evidence of reversals after buyer-initiated small trades in BOZ suggests that 60-day horizons may be sufficient to detect reversal.

ask spreads, where the premium from providing liquidity may be greater. Our results collectively support the idea that retail limit orders provide liquidity and benefit from the gradual reversal of price pressure, whereas market orders convey fundamental information and benefit as it is fully incorporated in prices.

While a large empirical literature categorizes retail investors as unsophisticated, behaviorally biased, and otherwise uninformed,[3] our paper joins a budding minority that portrays them in a more positive light. Our support for the information hypothesis is consistent with Kaniel, Liu, Saar, and Titman (2008) (hereafter KLST) and Griffin, Shu, and Topaloglu (2010), who find evidence that retail trading predicts returns around certain corporate events such as earnings and takeover announcements. The information story is plausible because the stock market can aggregate information from diverse sources, such as rank-and-file employees' and consumers' knowledge of products' strengths and flaws. Market prices may not immediately incorporate information from retail order flow because it is not publicly available.

Our support for the liquidity hypothesis is consistent with KST, who offer this explanation for cross-sectional return predictability in their New York Stock Exchange (NYSE) audit trail data, and KLST, who argue that liquidity provision explains half of the return predictability around earnings announcements. Although the liquidity provision and autocorrelated flow hypotheses are both based on the premise that trades initiated for non-informational reasons sometimes exert temporary pressure on stock prices, they differ in whether retail traders or institutional traders are displacing prices. Given the predominance of institutional trading in the US, one could argue that institutions are more likely to affect prices. If retail traders provide liquidity to these institutions, they can benefit from the reversal of price pressure.

[3] Examples include studies by Odean (1998), Barber and Odean (2000), and Benartzi and Thaler (2001).

As a whole, our findings complement those in KST and KLST in two main respects. First, because we distinguish individuals' market and limit orders, we can provide evidence that the two order types predict returns for different reasons. Most notably, limit orders do not predict the tone of news stories, whereas market orders do. In addition, limit orders are contrary to daily returns, whereas market orders are not.

Second, our detailed data on order types and brokers routing to our two market centers allow us to rule out two closely related alternative explanations for the findings in the KST and KLST studies. Specifically, while sophisticated broker-dealers may selectively trade against the least predictive order flow in their own accounts and route the remaining highly predictive order flow to market centers such as ours or the NYSE (Battalio and Loughran (2008)), we find no evidence that this practice explains any of the patterns discussed above. Our database is also not subject to BOZ's critique of the KST database: although most discount brokerages catering to self-directed individual investors route fewer than 1% of orders to the NYSE, Rule 606 disclosures reveal that such discount brokerages route large fractions of their orders to our market centers during our sample.[4]

Several of our findings are also consistent with those in Dorn, Huberman, and Sengmueller's (2008) study of individuals with accounts at a German discount broker. They show that both market and limit order imbalances predict increases in returns in the next week and that both imbalance types exhibit significant persistence. Based on these findings, they explain return predictability from market orders as "presumably due to persistent speculative price pressure." By contrast, we interpret return predictability from market orders as evidence of

[4] A third difference is that we find that retail investors trade in the same direction as the past content of news—*e.g.*, they sell after negative news. We have considerable power to detect this behavior because we use a comprehensive source of news data, rather than focusing solely on earnings announcements as KLST and most other studies do.

private information. This difference in interpretation arises from our two explicit tests of the autocorrelated flow hypothesis that are not explored in their study.

Our results also contribute to a growing literature examining the tone of financial news events. In our analysis, we combine the negativity measures used in Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), and Loughran and McDonald (2010). The latter two studies show that increases in these negativity measures are associated with decreases in firms' fundamental values, motivating news negativity as a proxy for changes in fundamentals.[5] We conduct similar validation tests for our sample using earnings surprises in Section 2.C.

An overview of the paper follows. Section 1 describes our data on individual orders and news stories. Section 2 presents our two main cross-sectional regressions in which we use retail imbalances to predict returns and the negativity of news stories. This section also includes our test of whether imbalances predict earnings surprises. Section 3 analyzes whether retail imbalances depend on past returns and past negativity. Section 4 provides further tests of the autocorrelated flow story, along with tests of alternative hypotheses based on selective order routing and execution. We discuss our results and conclude in Section 5.

1. Data on Retail Orders and News Stories

This section describes our sources for data on retail orders and news stories. Our trading data include all orders in common stocks listed on the NYSE, Nasdaq, and American Stock Exchange (AMEX) routed to our market centers from February 26, 2003 through December 31, 2007. Our market centers began as trading platforms for retail broker-dealers to route their orders, but they now also attract some institutional order flow.

[5] Recent studies of short selling activity by Engelberg, Reed, and Ringgenberg (2010) and Fox, Glosten, and Tetlock (2010) use a similar identification approach.

Broker-dealers' Rule 606 reports filed under the Securities and Exchange Commission's (SEC) Regulation National Market Systems (RegNMS) reveal that most large retail brokers route significant order flow to our market centers, including four of the top five online brokerages in 2005. In the quarter closest to 2005:Q1 where Rule 606 data are available for NYSE (Nasdaq) stocks, these four brokers route an average of 41% (35%) of their orders to our two market centers. Some of these brokers execute much of their remaining order flow internally, whereas other brokers do not internalize any order flow. We explicitly address concerns about selective order routing in Section 4.

Rule 606 disclosures indicate that most brokers receive small payments for directing marketable orders to our market centers. Such payments, between over-the-counter market makers and brokers who handle mostly retail order flow, are common. As an example, for marketable orders between 1000 and 1999 shares in Nasdaq-1000 securities routed by one of the top five brokers to our market centers in 2004:Q4, the market centers pay the broker 20% of the bid-ask spread up to a maximum of $0.015 per share. Based on these internalization and payment for order flow policies, one might infer that our market centers' order flow is uninformed. For example, Battalio and Loughran (2008) argue that:

> "payment for order flow and internalization survive on the ability to avoid trading with those who know where the stock price is headed (i.e., informed traders). Purchasers and internalizers of order flow profit by executing presumably uninformed orders at quotes posted by market makers seeking to protect themselves against trading with better-informed parties." (page 40)

Our tests below empirically evaluate whether this retail order flow is informed.

The retail order data include a code that classifies the order submitter as an individual or an institution based on how orders are submitted and routed. During our sample, over 225 million retail orders are executed at our market centers in exchange-listed stocks, resulting in

$2.60 trillion in volume. Databases of retail trades approaching this size are studied in Griffin, Harris, and Topaloglu (2003) (165 million trades), KST ($1.55 trillion traded), and BOZ ($128 billion traded).[6] The aggregate dollar value of $2.60 trillion in our sample is a significant percentage (2.3%) of listed (NYSE/AMEX/Nasdaq) volume. The average trade size is $11,566, which is between the average size of buys ($11,205) and sells ($13,707) in the Barber and Odean (2000) database from a discount broker. Our average trade size is roughly 30% lower than the averages in Barber and Odean (2008) and Kaniel, Saar, and Titman (2008), possibly reflecting the difference between clientele at discount brokers and full-service brokers.

Our main retail trading variable is daily order imbalance, measured using buys minus sells divided by buys plus sells. This variable uses quantities of buy and sell orders, but the results are robust to using numbers of buy and sell orders instead. The results are also similar for alternative imbalance measures, such as retail dollar imbalances divided by a moving average of total dollar volume or retail share imbalances divided by total shares outstanding. Our quantity-weighted average of retail imbalances is a natural way to aggregate retail investors' opinions.

We compute separate order imbalances for marketable (*Mkt*) orders, nonmarketable limit (*NmL*) orders, and executed limit (*XL*) orders. All market orders are classified as marketable. We determine whether a limit order is marketable using best bid and ask quotes at the exact time of order submission, which are provided by our market centers. If the limit buy (sell) price is at least as high (low) as the current best ask (bid), the limit order is marketable. All orders that are not marketable are classified as nonmarketable orders, except that we exclude nonmarketable buy (sell) orders that are not within 25 percent of the best bid (ask). This exclusion is designed to

[6] A study by Tetlock (2010a) uses roughly one quarter of our order data in two tests supporting its thesis that some individuals respond to stale news. This study does not directly address return predictability from retail trades.

eliminate economically unimportant quotes. Any nonmarketable limit order that is partially filled is defined as executed.

We compute order imbalances for each order type in which at least five orders occur in a stock on a day. The number of market orders (178 million) exceeds the numbers of both nonmarketable (115 million) and executed limit orders (47 million). We concentrate on market and nonmarketable orders because these represent active decisions by individuals, whereas the execution of limit orders depends on decisions by other traders who may not be retail investors.

We measure firm-specific news events using the DJ archive as described in Tetlock (2010b). It includes all DJ newswire and all *Wall Street Journal* (*WSJ*) stories about US firms traded on the NYSE, AMEX, or Nasdaq during our 2003 to 2007 sample. Our news data consist of 3.73 million newswires with 735 million words. We use the DJ firm code identifier in each newswire to assess whether a story mentions a publicly traded US firm. To ensure that news content is highly relevant to the firm, we use only stories mentioning at most two US firms and three total firms. On a typical (median) trading day during our sample, there are 4,716 public firms and 1,016 firms mentioned in DJ news. In a typical month during our sample, 95% of firms have DJ news coverage. This high news coverage allows us to measure the content of news much more frequently than quarterly for most firms.

For many news stories, DJ releases multiple newswire messages corresponding to paragraphs in the full story. Our measure of news for firm i on day t is a variable ($News = 0$ or 1) indicating whether firm i's DJ code appears in any newswires between the close of trading day $t - 1$ and the close of trading day t. We match the DJ firm codes to NYSE, Nasdaq, and AMEX ticker symbols in the Center for Research on Securities Prices (CRSP) database by date.

We measure the tone of firm-specific news by the fraction of words in the firm's stories on trading day *t* that are negative according to two psycholinguistic dictionaries. As shown in Tetlock (2007) and elsewhere, fluctuations in negative words are associated with stronger market reactions and bigger changes in earnings than changes in positive words. We use three negativity measures for robustness: *H4Neg* based on the Harvard-IV psychosocial dictionary used in Tetlock (2007), *FinNeg* based on Loughran and McDonald's (2010) financial dictionary, and *Neg* which is an average of *H4Neg* and *FinNeg* with weightings of 1/3 and 2/3.

The weightings in *Neg* adjust for the different scales of *H4Neg* and *FinNeg*. There are approximately twice as many negative words in the *H4Neg* list (4,187 versus 2,337). The overlap in the word lists is 1,121. We demean all negativity measures by day to facilitate comparisons between firms with news and those without news. This convention allows us to set negativity equal to zero on non-news days without affecting our results.

Panel A in Table I presents the daily cross-sectional distributions for order imbalance, news, and stock return variables. In this table, we use the sample restrictions for market order imbalances when computing statistics for the news and return variables. Panel A reports the distributions of the three raw negativity measures—*i.e.*, before we demean them. It shows that the interquartile range (IQR) of *RawH4Neg* is roughly twice as large as the IQR of *RawFinNeg*, which is consistent with the different numbers of words. Between the 5th and 95th percentiles, the range of *RawNeg* is 0.059, but the range of *Neg* is only 0.019 because it includes firms that do not have news stories. As expected, all three order imbalance measures have means and medians that are close to zero; and the 5th and 95th percentiles are near -1 and +1, respectively.

[Insert Table I]

Panel B in Table I shows daily cross-sectional correlations. We supplement our news and order data with standard variables from CRSP, including firm size (*MarketEquity*), ratio of book-to-market equity (*Book-to-Market*), and past daily, weekly, and monthly returns (*Ret*[0], *Ret*[-5,-1], and *Ret*[-26,-6]).[7] Controlling for returns at each of these horizons is important, as shown in Gutierrez and Kelley (2008). Size is the natural log of market equity from the most recent June. Book-to-market equity is the log of one plus book equity from the most recent fiscal year-end scaled by market equity from the previous December. Holding period returns are raw daily returns compounded over the specified horizons. We denote variables measured from day $t + x$ through day $t + y$ using the suffix [x,y] or just [x] if $x = y$. We include the most important control variables in Panel B. We exclude securities other than common stocks listed on the NYSE, Nasdaq, and AMEX and stocks with prices less than $1 at the previous month-end.

The univariate correlations are an informal preview of some results. Market orders exhibit significant positive correlations of 0.059 with current daily returns (*Ret*[0]) and 0.009 with past daily returns (*Ret*[-1]) but a negative correlation of -0.014 with past weekly returns (*Ret*[-5,-1]). Nonmarketable limit orders have significantly negative correlations of -0.128, -0.039, and -0.057 with current returns, past daily returns, and past weekly returns, respectively. These findings suggest that market order imbalances increase after positive daily returns, whereas limit order imbalances decrease.

All three daily negativity measures display similar correlations with current returns, ranging from -0.025 to -0.029, and high correlations with each other, ranging from 0.682 to 0.958. All three daily negativity measures are negatively correlated with market orders, with correlations between -0.010 and -0.009, and nonmarketable limit orders, with correlations

[7] In other specifications, we include control variables for abnormal trading volume, idiosyncratic volatility, and extreme returns. We do not report these tests because the main results do not change by a material amount.

between -0.004 and -0.001. Because our three negativity measures always produce similar correlation and regression estimates, we report only the results from our combined daily negativity measure (*Neg*[0]) in all subsequent tables. Past weekly negativity (*Neg*[-5,-1]) has a significant negative correlation of -0.006 with current returns, consistent with moderate return predictability found in Tetlock, Saar-Tsechansky, and Macskassy (2008).[8]

2. Predicting the Cross-Section of Returns and the Tone of News

Now we examine whether retail order flow predicts stock returns and the tone of firm-specific news stories. For all tests throughout the paper, we use daily cross-sectional ordinary least squares regressions in the spirit of Fama and MacBeth (1973). Point estimates are the time series averages of the daily regression coefficients. Standard errors employ the Newey-West (1987) correction for autocorrelation in the time series of the Fama-MacBeth regression coefficients. We set the number of lags in this procedure conservatively at two times the number of days in the dependent variable in each regression.

A. Predicting Returns Using Retail Order Imbalances

Our regression model for predicting holding period returns during days [*x*,*y*] is:

$$Ret[x,y] = b_0 + Imbalance[0] * b_1 + LagRet * b_2 + FirmChars * b_3 + e_0 \qquad (1)$$

Equation (1) includes control variables for firm size, book-to-market equity, and past returns because these are known predictors of returns. The *LagRet* matrix consists of three columns representing *Ret*[0], *Ret*[-5,-1], and *Ret*[-26,-6]. The *FirmChars* matrix consists of two columns

[8] There are few notable correlations between firm size and book-to-market equity and the order imbalance and negativity variables. One exception is the positive correlation of 0.124 between size and negativity. This could arise because small firms are more likely to appear in the news when they experience a positive event, whereas large firms appear in the news whenever they experience any material event.

representing *MarketEquity* and *Book-to-Market*. Our primary interest is return predictability coefficient b_1 on *Imbalance*[0].

The three Panels in Table II report regression estimates for retail imbalances based on market orders and nonmarketable limit orders and for raw returns and risk-adjusted returns. Our measure of risk-adjusted returns is *CAR*[*x*,*y*], which is the difference between the stock's realized return during days [*x*,*y*] and the stock's expected return using the Fama-French (1993) three-factor model. The expected return is based on rolling estimates of each stock's market, size, and book-to-market betas during days [-257,-27], approximately eleven months of data, and realized market, size, and book-to-market factor returns during days [*x*,*y*]. The holding periods included in Table II are days [1], [2,5], [6,10], [11,20], [21,40], and [41,60]. Only Panel A in Table II reports the coefficients on control variables.

[Insert Table II here.]

The main result is that market and nonmarketable limit orders both positively predict returns at daily, weekly, monthly, and quarterly horizons. All daily and weekly results are statistically significant at the 1% level; and most long-horizon results are significant at the 5% level. The economic magnitude of these results is substantial. In Panel A with raw returns, the sums of the b_1 coefficients from days 1 through 20 are 35.7 basis points (bps) for market orders and 30.2 bps for nonmarketable limit orders. To compare these results to KST, we convert these sums into annualized returns on long-short portfolios formed based on daily imbalance deciles with midpoints at the 5th and 95th percentiles. Multiplying the sums by (252/20) and by the appropriate range of each order imbalance type, we estimate the annual long-short returns on the portfolios formed on daily market and nonmarketable limit order imbalances to be 8.03% and

7.20%, respectively. As shown in Panels B and C, we obtain nearly identical risk-adjusted estimates of returns.[9]

Panels B and C also reveal that retail market and limit order imbalances *positively* predict risk-adjusted returns during days [21,40] and [41,60]. Three of these four return predictability coefficients are statistically significant at the 5% level and two are significant at the 1% level. Based on the 95% confidence interval on the sum of these coefficients, we can actually *reject* the hypothesis that return predictability from retail imbalances reverses during days [21,60].

The inclusion of the control variables does not materially affect the coefficients on imbalances. Daily and weekly return reversals are statistically significant but economically much smaller than the predictability from retail order imbalances. For example, the one-day predictability from an IQR change in market order imbalances is 9.8 * (0.313 – (-0.466)) = 7.6 bps, whereas the one-day predictability from daily return reversal is only -132.9 * 0.023 = -3.1 bps, where 0.023 is the IQR of daily returns. The size and book-to-market coefficients have the expected signs—negative and positive, respectively—but are economically insignificant predictors of returns at most horizons.

In summary, the regressions in this subsection demonstrate that both market order and nonmarketable limit order imbalances positively predict stock returns at horizons up to 20 days. This is consistent with Dorn, Huberman, and Sengmueller (2008), KST, and BOZ. Our statistical rejection of return reversal during days [21,60] is somewhat unexpected in light of previous results in BOZ, which is based on data before 2000. We investigate this further by asking whether imbalances predict information about fundamentals.

[9] Only the quarterly result for nonmarketable limit orders is sensitive to the measurement of returns: it is insignificantly positive with raw returns but significantly positive with abnormal returns. The relatively low market betas for stocks with buy imbalances in *NmL* orders gives rise to the discrepancy.

B. Predicting News Negativity Using Retail Order Imbalances

Here we test the private information hypothesis by examining whether retail order imbalances predict news events. Our model for predicting news negativity during days [*x*,*y*] is:

$$Neg[x,y] = c_0 + Imbalance[0] * c_1 + LagNeg * c_2 + LagRet * c_3 + FirmChars * c_4 + e_1 \qquad (2)$$

Equation (2) includes control variables for firm size, book-to-market equity, and past returns because these are known predictors of negativity. The *LagRet* and *FirmChars* matrices are defined as before. Including control variables for past returns is necessary because both negativity and order imbalances may depend on past returns.[10] Importantly, the *LagNeg* matrix includes controls for lagged negativity from days [0], [-5,-1], and [-26,-6] because the tone of news exhibits moderate persistence. Our primary interest is the negativity predictability coefficient c_1 on *Imbalance*[0].

[Insert Table III here.]

Table III reports regression estimates for retail imbalances based on market orders and nonmarketable limit orders. The negative and significant coefficients on *Imbalance*[0] in the first four columns show that market order imbalances negatively predict news negativity at the daily, weekly, and monthly horizons. That is, more retail buying on day [0] is associated with *less* negativity in future news stories. The imbalance coefficient is long-lasting and economically large compared to coefficients on other predictors of negativity, such as daily returns (*Ret*[0]). Daily returns no longer predict negativity during days [11,20], whereas the coefficient on imbalances decreases by only 30% of its day [1] value during days [11,20]. The magnitude of the day[0] coefficients on market order imbalance and returns are -0.00010 and -0.00128. Increasing the independent variables, market *Imbalance*[0] and *Ret*[0], from the 5th to the 95th percentile produces changes in the dependent variable, *Neg*[1], equal to -0.94% and -0.57% of its 5th-to-

[10] We explicitly analyze the dependence of order imbalances on past returns in Section 3.A.

95th percentile range.[11] Interpreting this magnitude is difficult because the variance (and range) of the dependent negativity variable includes an unknown amount of measurement error.

Nonmarketable limit order imbalances, however, do not significantly predict negativity in either the positive or negative direction at any time horizon. Even the 99% confidence intervals on the limit order coefficients are sufficiently narrow to rule out economically large estimates, such as the values of the coefficients on market orders. These findings suggest that market order imbalances predict future news events, whereas limit order imbalances do not.

This is somewhat surprising given the results in Table II showing that nonmarketable limit order imbalances are actually slightly better predictors of future returns. The inability of limit orders to predict news events also seems inconsistent with two previous empirical studies. In experimental markets, Bloomfield, O'Hara, and Saar (2005) show that traders with information about fundamentals use limit orders more often than other traders. Kaniel and Liu (2006) argue that, in theory and practice, informed traders with long-lived information are likely to use limit orders. One way to reconcile these two studies with our finding in Table III is that retail traders may not have sufficiently long-lived information to justify the use of limit orders.

[Insert Figure 1 here.]

Figure 1 summarizes the ability of daily market and limit orders to predict returns and news negativity at horizons of days [1], [2,5], [6,10], and [11,20]. The figure is based on standardized values of the regression coefficients on daily imbalances in Tables II and III. The key point is that both market and limit orders predict returns, but only market orders predict the negativity of news.

---

[11] For imbalances, the calculation is -0.00010*(0.846 – (-0.940)) / 0.019 = -0.94%. For returns, it is -0.00128*(0.045 – (-0.039)) / 0.019 = -0.57%.

C. Predicting Earnings Surprises

To assess the robustness of our results on predicting negativity, we now test whether market and limit order imbalances predict earnings surprises, as measured by the sign of analysts' forecast errors. Because firms announce earnings much less often than they appear in the news, this test has much lower statistical power than our negativity results in Table III. But using a well-established measure of changes in firms' fundamental values, such as earnings surprises, has two offsetting benefits. First and foremost, we can assess whether market and limit order imbalances predict earnings surprises in a manner that is consistent with their predictive power for negativity. Second, we can show that our negativity measure predicts earnings surprises in our sample, much like Tetlock, Saar-Tsechansky, and Macskassy (2008).

The variable indicating the sign of the earnings surprise, if any, between days *x* and *y* is *SignFE*[*x*,*y*]. The earnings announcement date is the earlier of that reported by Institutional Brokers' Estimate System (I/B/E/S) and Compustat, and the surprise is the difference between actual quarterly earnings and the median forecast obtained from I/B/E/S. We use the following regression model to predict earnings surprises during days [*x*,*y*]:

$$SignFE[x,y] = d_0 + Imbalance[0] * d_1 + LagRet * d_2 + LagNeg * d_3 + FirmChars * d_4 + e_1 \quad (3)$$

Equation (3) includes control variables for past returns, past negativity, and firm characteristics. All independent variables in Equation (3) are the same as those in our Equation (2) model for predicting negativity.

[Insert Table IV here.]

Table IV reports the coefficient estimates on all coefficients, including the key coefficients on daily imbalances, for both market and limit order imbalances at horizons of days [1], [2,5], [6,10], and [11,20]. The main result is that market order imbalances positively predict earnings surprises during days [1,20], whereas limit order imbalances only positively predict earnings surprises on day [1] and actually negatively predict surprises during days [11,20]. Comparing the sum of the predictability coefficients across days [1,20] produces striking differences: the market order coefficients sum to 0.780, which is statistically significant at the 1% level; the limit order coefficients sum to 0.184, which is statistically insignificant. In other words, daily retail market order imbalances have over four times more predictive power for earnings surprises during the next 20 days. These results are consistent with the hypothesis that retail market orders aggregate private information about fundamentals but are inconsistent with the hypothesis that limit orders are informed.

Rows two, three, and four in Table IV indicate that news negativity negatively predicts the sign of earnings surprises at virtually all horizons. Of the 15 negativity coefficients, 14 are negative and statistically significant at the 1% level.[12] Overall, the findings in Table IV provide strong support for the use of news negativity as a proxy for changes in firms' fundamentals. We find qualitatively consistent results in unreported tests that use firms' returns on news days as a third proxy for firms' fundamentals. Specifically, the coefficients on market order imbalances in regressions predicting firms' news-day returns at the daily and weekly horizons are 61% and 71% higher than the corresponding coefficients on limit order imbalances.

3. Liquidity Provision and Return Predictability from Retail Order Imbalances

Although Table II shows that market and limit orders both predict 20-day returns with comparable magnitudes, the results in Tables III and IV reveal that only market orders predict the tone of news. A natural inference is that market orders predict returns because they are

[12] The exception is that daily negativity (*Neg*[0]) is an insignificant predictor of the next day's forecast error. But this specification already includes *Neg*[-5,-1] and *Neg*[-26,-6], which are both strong negative predictors of earnings.

informed, whereas limit orders may be providing liquidity. We further evaluate this preliminary interpretation using two sets of tests in this section. First, we examine how return predictability from retail orders varies across stocks with different bid-ask spreads. Second, to see whether retail orders of different types could offset liquidity shocks, we analyze whether returns and news forecast order imbalances.

A. Return Predictability from Retail Order Imbalances in Stocks with Differing Liquidity

The first test adds an interaction term between stock liquidity and retail order imbalances to the return predictability regressions in equation (1). Our liquidity variable is equal to either -2, -1, 0, +1, or +2 based on a stock's bid-ask spread quintile, according to daily sorts of share-weighted percentage spreads at order submission for each order type. The best bid and ask at order submission are provided by our market centers.[13] In these tests, we control for the direct effect of the spread quintile variable, an interaction between spreads and daily returns, and an interaction between retail imbalances and firm size, as measured by a size quintile variable ranging from -2 to +2.

[Insert Table V here]

The results from regressions predicting returns during days [1], [2,5], [6,10], and [11,20] appear in Table V below. The key finding is that, consistent with liquidity provision, retail limit orders are stronger positive predictors of returns in stocks with higher bid-ask spreads. The sum of the interaction coefficients from days 1 through 20 is 18 bps and is highly statistically significant at the 1% level at all horizons. This magnitude implies that return predictability from retail limit orders is equal to -6 bps, 30 bps, and 66 bps in stocks in spread quintiles -2, 0, and +2.

[13] To eliminate potentially erroneous quotes, we retain orders only if both closing quotes and NBBOs at the time of order submission satisfy three conditions: (1) the ask exceeds the bid; (2) the ask is at most 150% of the bid; (3) the absolute value of returns based on the quote midpoints does not exceed 30%.

By contrast, the interaction term between bid-ask spreads and market order imbalances is only positive during the first week and its 20-day sum (3 bps) is six times smaller than the sum of the limit order interaction coefficients.

B. Daily Regressions Predicting Retail Order Imbalances

Next we explore whether retail market and limit order imbalances seem to respond to past liquidity shocks. Our regression model for predicting retail imbalances on day [1] is:

$$\begin{aligned} Imbalance[1] = f_0 + LagImb * f_1 + LagRet * f_2 + LagNeg * f_3 + FirmChars * f_4 \\ + NewsVars * f_5 + EarnAnnVars * f_6 + e_1 \end{aligned} \tag{4}$$

Equation (4) includes control variables for past imbalances, past returns, past negativity, firm characteristics, and for variables representing past news and earnings announcements. The *LagImb* matrix includes controls for past imbalances during days [0], [-5,-1], and [-26,-6] because imbalances are somewhat persistent. The *LagRet*, *LagNeg*, *FirmChars* matrices are defined as before. The *NewsVars* matrix consists of the news dummy (*News*[0]) and its interactions with *Imbalance*[0] and *Ret*[0]. The *EarnAnnVars* matrix consists of an earnings announcement dummy (*Earn*[-*1*,*0*]), its interactions with *Imbalance*[0] and *Ret*[0], and the sign of the earnings surprise (*SignFE*[-*1*,*0*]).

Table VI reports all regression coefficients above for imbalance measures based on three order types and for two regression specifications. We focus on the coefficients (f_1) on *LagRet*, but several other coefficients are interesting, including coefficients f_3, f_5, and f_6 on *LagNeg*, *NewsVars*, and *EarnAnnVars*. The three types are market (*Mkt*), nonmarketable limit (*NmL*), and executed limit (*XL*) orders; and the two specifications either include or exclude the *EarnAnnVars* matrix. We include executed limit orders to facilitate comparisons with KLST.

[Insert Table VI here.]

The main finding in Table VI is that retail imbalances in the three different order types exhibit very different responses to past daily returns (*Ret*[0]). Retail traders submitting market orders are slight net buyers of stocks experiencing positive returns on the prior day, whereas retail traders submitting nonmarketable limit orders are significant net sellers of these stocks. This contrast highlights the importance of distinguishing market and limit orders. A comparison of the *Ret*[0] coefficients in the *NmL* and *XL* columns reveals that separately analyzing nonmarketable and executed limit order imbalances is also important because their dependence on past returns differs dramatically. Executed limit order imbalances may be driven by the decisions of aggressive institutional traders. In this interpretation, aggressive institutional traders would be net buyers of stocks with positive returns on the prior day, which would be consistent with the evidence in Griffin, Harris, and Topaloglu (2003).

Another notable result in Table VI is that both market and nonmarketable limit order imbalances decrease in response to high past negativity in news stories. That is, both market and limit order imbalances trade in the same direction as the tone of past news, which we define as news momentum trading. This result holds for past news negativity at daily [0], weekly [-5,-1], and monthly [-26,-6] horizons. Considered together, the coefficients on *Ret*[0] and *Neg*[0] in the *NmL* column show that limit order imbalances move in the opposite direction of past returns but do not oppose the direction of past news.

One natural interpretation is that retail limit orders provide liquidity in response to return shocks that are *not* driven by news. There is no such pattern for retail market orders. To test this interpretation, we analyze retail traders' behavioral response to market returns on news days. The interaction coefficient between our news dummy variable and returns on the day of news

(*News*[0]**Ret*[0]) captures the differential response of imbalances to returns on news days versus non-news days. It reflects return momentum trading on news days, which is distinct from news momentum trading as defined above. Although the *News*[0]**Ret*[0] interaction coefficient is significantly positive for nonmarketable limit orders, suggesting return momentum behavior, it is highly negative for market order imbalances, suggesting return contrarian behavior.

The positive interaction coefficient for limit orders (only) is consistent with our initial interpretation: limit orders provide liquidity in response to return shocks in the absence of news. These results complement earlier evidence in Table III, which shows that limit orders do not predict news negativity, whereas market orders do. While Table III suggests that limit orders are not based on private information, Table VI suggests that they do provide liquidity. Similarly, Table III implies that market orders are based on private information and Table VI suggests that they do not provide liquidity.

Our finding that individuals submit orders that are consistent with the direction of the content of news—*i.e.*, news momentum behavior—is robust across both market and nonmarketable orders and at all horizons. In a related test, KLST find that individuals' trades oppose the direction of past earnings surprises. The negative coefficients on past news negativity in Table VI are not necessarily inconsistent with KLST's finding. To explore this issue, we separately identify news events corresponding to earnings announcements using the *Earn* dummy and include *SignFE*[-1,0] as a measure of earnings surprise. The coefficient on *SignFE*[-1,0] in Columns 2, 4, and 6 in Table VI is significantly negative for all three order types. This suggests that individuals in our data trade against earnings surprises just as in KLST. It also shows that news momentum or contrarian behavior depends on the definition of news. Because most news stories do not coincide with earnings announcements, many possible explanations exist. The simplest is that individuals' responses to a typical news story differ from their responses to earnings news. A detailed analysis of this and other explanations is beyond the scope of this paper.

The coefficients (f_1) on the lagged imbalances variables are consistently and significantly positive, ranging from 0.108 to 0.225. This is consistent with prior evidence on retail imbalances. We exploit this fact in subsequent tests in Section 4.A.

B. Intraday Analysis of Imbalances and Returns

We now analyze the relationship between imbalances and intraday returns. For each order, we split the day into two parts and compute returns before and after the order is submitted. The variable *RetPreO* is the return from the prior day's closing quote midpoint to the quote midpoint at the time the order is submitted. The variable *RetPostO* is the return from the quote midpoint at the time of the order to the same day's closing quote midpoint. Closing quotes are from Trades and Quotes (CRSP) for NYSE and AMEX (NASDAQ) securities.

We multiply returns by the sign of the order (1 for buys, -1 for sells), compute a share-weighted average across all orders of a given type for each stock-day, and then average across stocks on each day. Table VII reports the time series average of this value as a summary of the relationship between order imbalance and pre- and post-order returns. A positive (negative) value can be interpreted as a positive (negative) covariance between order imbalance and the respective intraday return. For this analysis, we split marketable orders into true market orders and marketable limit orders; and we segregate nonmarketable limit orders into those priced within 10 cents of the inside quote (*near*) and all others (*far*).

[Insert Table VII here.]

The means of *RetPreO* in Table VII are all negative (-75.8 bps to -35.2 bps) for limit orders—even for marketable limit orders (-17.7 bps). However, the mean of *RetPreO* for market orders is significantly positive (10.6 bps). This demonstrates that our daily Granger-type causality results in Table VI generalize to intraday frequencies: again, limit orders are contrary to recent returns, whereas market orders exhibit return momentum.

For all but nonmarketable limit orders, *RetPostO* is decomposed into two additional components. The variable *HSpread* is the half-spread in percentage terms for market orders and the return computed from the quote midpoint to the limit price for executed limit orders. The variable *RetPostX* is a return computed from the bid (ask) price for market sell (buy) orders to the closing midpoint. It is computed from the limit price to the closing midpoint for executed limit orders. Assuming no price improvement, this return is the negative of a realized spread calculated through the end of the day. This is a proxy for market maker profits if we assume that market maker inventory is zero at the end of the day. These returns are aggregated across orders and stock-days like the other intraday returns.

Comparing bid-ask spreads in Table VII to return predictability in Table II, we infer that retail market orders held for 20 days or more could earn small excess returns even after trading costs. The average effective half-spreads at the time of order submission (*HSpread*) are 16 bps for both market and marketable limit orders. A 16 bps half-spread is slightly less than half of the magnitude of 20-day return predictability from a one-unit change in market order imbalances (35 bps). Assuming a 60-day holding period increases the magnitude of return predictability to 45 bps, implying an excess return of 13 bps after incurring a 32-bps round-trip trading cost.

Moreover, retail investors using market orders recover much of the one-way trading cost by the end of day 0 because these orders have positive intraday alphas, as shown by the difference between effective and realized spreads. Realized spreads (*RetPostX*) are 8.1 bps for market orders, 1.4 bps for marketable limit orders, 4.7 bps for executed far-from-market limit orders, and 2.3 bps for executed near-to-market limit orders. The fact that realized spreads are positive suggests that market makers profit by trading against all retail order types when daily buy and sell orders offset each other. Analyzing market maker profitability in the case where there is a net imbalance in daily buy and sell orders is not possible without knowing dealers' inventory management strategies and the costs of unwinding positions in interdealer transactions.

Figure 2 illustrates a striking similarity between the intraday and daily analyses. Panel A depicts the relations between *RetPreO* and *RetPostO* and different order types. Panel B shows analogous relations over days [-1,5] using long-short portfolios based on retail order imbalance deciles on day 0. The benchmark return comes from the Fama and French (1993) three-factor model. The figure shows that limit orders are associated with intraday and daily return reversals, whereas market orders are associated with intraday and daily return momentum. The positive return predictability from limit orders during days [1,5] is equal to a reversal of about one-third of the cumulative return during days [-1,0]. Collectively, the findings in Figure 2 appear most consistent with limit orders providing liquidity in response to recent price pressure, and market orders conveying private information that is gradually incorporated into prices.

[Insert Figure 2 here.]

4. Further Explanations for Return Predictability

This section further explores the autocorrelated flow hypothesis and two alternative hypotheses that may explain cross-sectional variation in return predictability from retail flow.

The alternative hypotheses are based on selective broker internalization of orders and adverse selection in limit order execution. These tests complement our earlier results.

A. The Autocorrelated Flow Hypothesis

The results in Panels A and B in Table II demonstrate that returns do not reverse at the quarterly horizon. This casts doubt on the autocorrelated flow hypothesis but is insufficient grounds for rejecting it altogether. In this subsection, we offer a complementary cross-sectional test based on the mechanism in the autocorrelated flow story.

We first establish that there is persistent cross-sectional variation in retail flow persistence for stocks. From the perspective of the autocorrelated flow hypothesis, this finding suggests that certain stocks are more prone to repeated buying pressure and repeated selling pressure from retail investors. If the autocorrelated flow hypothesis is correct, one would expect higher return predictability in stocks with persistently higher autocorrelation in retail flow. There should be both more initial return predictability and a larger reversal in such stocks. We focus on increases in the initial return predictability because we may lack sufficient statistical power to detect increases in reversals. This prediction highlights the fact that the autocorrelated flow hypothesis runs counter to a key idea in market microstructure theory: anticipated order flow should have a muted (or no) effect on prices. Theory predicts that market makers adjust prices in anticipation of positively autocorrelated retail flow (Chordia and Subrahmanyam, 2004). Our tests shed light on whether the autocorrelated flow hypothesis or traditional microstructure theory provides a better description of the data.

This test of the autocorrelated flow hypothesis uses a two-stage regression approach. In the first stage, for each stock in each quarter, we estimate imbalance persistence using time series regressions of daily retail market order imbalance on lagged daily retail market order imbalance. We use only market orders in the first stage for two reasons: BOZ argue that these orders exert the most pressure on prices; and we have more data on market orders, allowing for more precise estimates.

We sort stocks into quintiles based on the distribution of the persistence coefficients in each quarter. The mean of the persistence coefficients is 9% and the four quintile breakpoints are -4%, 5%, 12%, and 21%. More importantly for our purposes, the persistent coefficients themselves exhibit substantial persistence across non-overlapping quarters. A cross-sectional regression of current persistence on the previous quarter's (the two-quarters-ago) persistence produces a highly significant coefficient of 0.132 (0.058). We use these two coefficients to calibrate a first-order autoregressive model of imbalance persistence, which allows us to quantify the measurement error in persistence. We describe this procedure in the online Appendix available at http://www0.gsb.columbia.edu/faculty/ptetlock/papers/CrowdWisdomAppendix.pdf.

We interact our rolling estimates of the persistence coefficients from the quarter ending on day 0 with imbalances on day 0 in a second-stage cross-sectional return predictability regression. This second-stage regression is the same as the model in Equation (1), except that we include four variables related to imbalance persistence. A variable called *Persist* represents the five persistence coefficient quintiles using values of +2, +1, 0, -1, and -2.[14] The key variable is an interaction term between retail imbalances and persistence (*Imb*[0]**Persist*). The coefficient on this interaction will be positive if retail imbalances are better predictors of returns stocks with higher autocorrelation in retail flow. We also allow for interactions between persist and daily

[14] In the first stage regression, we keep only stocks with imbalance measures on at least 90% of the days during the estimation period and those for which the absolute value of the persistence coefficient is less than one. For all other stocks, we set *Persist* equal to zero.

returns (*Ret*[0]**Persist*) and between imbalances and a variable representing firm size quintiles (*Imb*[0]**SizeQuint*). The size quintile (*SizeQuint*) variable is equal to either +2, +1, 0, -1, and -2 depending on a firm's NYSE size quintile in the most recent June. The coefficient on the size interaction indicates whether retail return predictability is higher in small or large firms.

[Insert Table VIII here.]

Table VIII reports the unadjusted coefficient estimates on all variables. The main result is that the interaction between persistence and both market and nonmarketable imbalances (*Imb*[0]**Persist*) significantly positively predicts returns only at the weekly horizon. As explained in the online Appendix, accounting for measurement error in persistence increases our unadjusted interaction coefficients by 82%. Even after this adjustment, our point estimates indicate that the persistence in imbalances can explain only 26% (53%) of the return predictability from retail imbalances at the monthly (weekly) horizon. Although the point estimates for the interaction coefficients in weeks two through four are close to zero, the wide 95% confidence intervals do not allow us to reject economically large estimates. At the weekly horizon, however, the narrow confidence intervals imply that the autocorrelated flow hypothesis leaves a significant amount of return predictability unexplained. In unreported results, our findings are similar when we use additional liquidity control variables and when we omit all controls and use only the main imbalance, persistence, and interaction variables.

The significantly negative estimates of the coefficient on the size interaction with imbalances show that retail return predictability is higher in small firms, mainly during days [1,5] and [6,10]. This finding applies to both market and nonmarketable limit order imbalances. For market orders, one interpretation is that individuals are more likely to possess private information about small firms, possibly because institutions, stock analysts, and reporters gather substantial information about large firms. For limit orders, a natural interpretation is that individuals face less competition in providing liquidity in small firms, possibly because institutions are less likely to trade small stocks.

B. The Internalization Hypothesis

Another possible explanation for our return predictability findings is that only relatively well-informed orders are routed to market makers because the least informative order flow is internalized by retail brokerages. To explore this, we augment our cross-sectional return predictability regression in Equation (1) with four additional independent variables related to the extent of internalization by a subset of brokers routing to our market centers. Specifically, the data indicate which orders come from a group of brokers that internalizes according to their Rule 605 and 606 disclosures and which orders do not. The variable *InternRatio* summarizes the collective internalization practices of these brokers. It is defined for each stock-month and order type (market or limit) as the ratio of flow internalized as per Rule 605 disclosures to flow routed to our market centers.

We use this internalization ratio to construct four variables. The first is a 0 or 1 dummy indicating whether *any* brokerages internalize *any* orders of the order's type in the stock (*IntDum*) in the preceding month. Our second variable *IntQuint* is equal to -2, -1, 0, +1, or +2, based on a ranking of stocks into quintiles according to *InternRatio* in the preceding month. Our third and fourth internalization variables are interactions of *IntDum* and *IntQuint* with retail imbalances computed with orders from the subset of brokers in the same order type and stock, *Imb*[0]**IntDum* and *Imb*[0]**IntQuint*. We also include a size interaction with imbalances (*Imb*[0]**SizeQuint*) to ensure that estimates of the four internalization coefficients do not reflect an indirect effect of firm size. Because these regressions include only orders from a subset of brokers, we include stock-days for which there are at least two orders for each type rather than imposing the five-order filter in our main tests.

[Insert Table IX here.]

Table IX reports the coefficient estimates for the four internalization variables and all control variables. The six columns represent estimates for imbalances based on market and nonmarketable limit orders and for returns during days [1,5], [6,10], and [11,20]. Reassuringly, the six coefficients on retail market and nonmarketable limit imbalances remain positive in all specifications and are statistically significant at the 1% level in five specifications. One surprising finding is that 10 of the 12 the point estimates on the two interaction coefficients between internalization and imbalances (*Imb*[0]**IntDum* and *Imb*[0]**IntQuint*) are actually negative. Three of the 10 negative interaction coefficients are significant at the 5% level and neither of the two positive coefficients is significant at even the 10% level.

This implies that order flow routed to our market centers in stocks where brokers internalize more flow is actually less (not more) predictive of future returns. Not only does internalization fail to explain our main finding that retail order flow positively predicts returns, but brokers' internalization practices may actually reduce the predictability from retail flow routed to market centers. In this sense, our estimates of retail return predictability are conservatively low relative to estimates from a hypothetical data set that includes all order flow at brokerages routing to our market centers.

C. The Adverse Selection Hypothesis

Linnainmaa's (2010) study of Finnish data suggests another hypothesis that may explain cross-sectional variation in return predictability from retail flow: informed traders may selectively trade against limit orders, implying that imbalances in executed limit orders predict lower returns and more negative news than imbalances in other order types. Informed trading against stale limit orders may cloud the interpretations of studies unable to differentiate between order types. Unlike most other studies of US data, our data include order types, giving us an opportunity to assess the importance of selective trading against limit orders. Table X below reports the findings from using executed limit orders in the main return regressions in Equation (1). The dependent return variables are risk-adjusted returns during days [1], [2,5], [6,10], [11,20], [21,40], and [41,60] to allow for direct comparisons to Panels B and C in Table II.

[Insert Table X here.]

The main result in Table X is that the point estimates on the daily retail imbalance coefficient are all positive after day one. The days [2,5] and [6,10] coefficient estimates are both significantly positive at the 1% level. The magnitude of the negative coefficient on day [1] is quickly overwhelmed by the positive coefficients on days [2,5] so that the total return predictability on days [1,5] is significantly positive. These findings suggest that even executed limit orders submitted by retail investors exhibit positive return predictability, just like the other order types.

The quantitative magnitude, however, of predictability from executed limit orders is much lower than the magnitude from market orders and nonmarketable limit orders. The sum of the predictability coefficients for executed limit orders in days [1,20] is 11.9 bps, as compared to 35.5 bps for market orders and 42.0 bps for nonmarketable limit orders. The large difference between the magnitudes for executed limit orders and nonmarketable limit orders shows that the limit order effect in Linnainmaa (2010) is relevant for understanding retail return predictability. Still, we do not find *negative* expected returns for any order type. The relatively low returns for executed limit orders demonstrate that retail investors' active decisions, not their passive responses to institutional orders, generate the positive return predictability from retail orders.

5. Discussion and Analysis

We study extensive data on retail orders and news to contribute to the debate on whether and why individual investors can predict returns. We show that individuals positively predict returns at horizons up to 20 days and that return predictability does not reverse at the quarterly horizon. Both market and nonmarketable limit orders exhibit similar return predictability patterns. Yet the informational content of these two order types differs dramatically: retail market order imbalances predict the tone of news, but limit order imbalances do not. These findings significantly extend the results in KST and KLST. The differing results for market and limit orders underscore the importance of distinguishing order types, as emphasized in Dorn, Huberman, and Sengmueller (2008).

Our analysis of retail order flow, returns, and news sheds light on the merits of several explanations for return predictability that have contrasting implications for public policy and market structure. The liquidity provision and autocorrelated flow hypotheses make conflicting predictions about whether retail trading stabilizes or destabilizes market prices, particularly in illiquid markets. Our results are consistent with retail limit orders providing liquidity and stabilizing prices. Several tests cast doubt on the autocorrelated flow hypothesis for retail market and limit orders, suggesting retail traders are not a destabilizing influence on prices. A notable caveat is that our five-year database gives us limited statistical power to detect return reversal at horizons beyond quarterly.

Our results and those in KST and KLST based on post-2000 data show that aggregate retail order flow positively predicts the cross-section of returns, which contrasts with earlier evidence in Odean (1999), Barber and Odean (2000), and Barber and Odean (2002). Our finding that returns do not reverse at the quarterly horizon ostensibly disagrees with earlier evidence in BOZ's analysis of reversals during days [21,40] and [41,60] following net imbalances in small trades. We offer two possible reasons why active retail investors appear more sophisticated in the studies using retail investor data after 2000.

First, retail traders may have learned from their initial online trading experiences. Using Finnish data from 1995 to 2003, Seru, Shumway, and Stoffman (2010) show that skilled individuals learn to increase their trading activity, while unskilled individuals learn to trade less actively or stop trading altogether. Second, the relative wealth of less sophisticated retail traders may have declined significantly since 2000. For example, an investor holding the Nasdaq Composite Index in March of 2000 would have lost 60% of his stock wealth in one year and over 75% by October of 2002. Two trends documented in French (2009) could be related to the increasing sophistication of retail investors: direct individual ownership in US stocks decreases from 36.2% in 2000 to 21.5% in 2007, while holdings in foreign stocks increase from 13.7% to 27.2% of US investors' portfolios. Detailed data on individual investors would allow for tests of these conjectures.

Our return predictability findings imply that observing retail order flow is a valuable privilege for market makers because it can help them predict stock returns beyond one trading day. This idea could explain why many retail market makers pay for retail order flow. In fact, our estimates suggest that bid-ask spreads are smaller in magnitude than return predictability from retail flow, implying the latter is a bigger potential source of market maker profits. Some industry analysts offer a similar explanation for why Citadel, a high-frequency trading firm, negotiated a deal with a large discount retail broker in which the broker would route 97.5% of its customers' Nasdaq trades to Citadel's market maker:

> "... in the high-frequency game it's all about getting as much customer 'order flow' as possible. That's because the algorithmic programs that drive high-frequency trading desks, both for market makers and prop desks, are designed to anticipate trends in prices of stocks, options and commodities. The more trades these sophisticated machines get to see, the better they become at predicting price trends and making money for their creators." (*Reuters: Commentaries*, August 14, 2009, "E*Trade: Citadel's Bonanza," by Matthew Goldstein)

Future work should test the idea that broker-dealers value order flow for its predictive ability.

The leading interpretations of our two main findings are that retail investors using market orders aggregate information and those using limit orders provide liquidity when its supply is limited. The aggregated decisions of these retail investors are "wise" in two respects: they positively predict the cross-section of stock returns and they improve the informativeness of prices. These results certainly do not overturn the vast literature on individual behavioral biases. They do, however, demonstrate that a crowd of retail investors can be wiser than its individual members.

References

Barber, Brad M., and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773-806.

Barber, Brad M., and Terrance Odean, 2002, Online investors: Do the slow do first? *Review of Financial Studies* 15, 455-488.

Barber, Brad M., and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785-818.

Barber, Brad M., Yi-Tsung Lee, Yu-Jane Liu, and Terrance Odean, 2009, Just how much do individual investors lose by trading? *Review of Financial Studies* 22, 609-632.

Barber, Barber M., Terrance Odean, and Ning Zhu, 2009, Do retail trades move markets? *Review of Financial Studies* 22, 151-186.

Battalio, Robert H., and Tim Loughran, 2008, Does payment for order flow to your broker help or hurt you? *Journal of Business Ethics* 80, 37-44.

Benartzi, Shlomo, and Richard H. Thaler, 2001, Naive Diversification Strategies in Defined Contribution Savings Plans, *American Economic Review* 91, 79-98.

Bloomfield, Robert, Maureen O'Hara, and Gideon Saar, 2005, The 'make or take' decision in an electronic market: Evidence on the evolution of liquidity, *Journal of Financial Economics* 75, 165-199.

Chordia, Tarun, and Avanidhar Subrahmanyam, 2004, Order imbalance and stock returns: Theory and evidence, *Journal of Financial Economics* 72, 485-518.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2008, Correlated trading and returns, *Journal of Finance* 58, 885-920.

Engelberg, Joey, Adam V. Reed, and Matthew Ringgenberg, 2010, How are shorts informed? Short sellers, news, and information processing, University of North Carolina working paper.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, Return, and Equilibrium: Empirical Tests, *Journal of Political Economy* 81, 607-636.

Fox, Merritt B., Lawrence R. Glosten, and Paul C. Tetlock, 2010, Short selling and the news: A preliminary report on an empirical study, *New York Law School Law Review* 54, 129-171.

French, Kenneth R., 2008, The cost of active investing, *Journal of Finance* 58, 1537-1573.

Griffin, John M., Jeffrey H. Harris, and Selim Topalaglu, 2003, Dynamics of institutional and individual trading, *Journal of Finance* 58, 2285-2320.

Griffin, John M., Tao Shu, and Selim Topaloglu, 2010, Examining the dark side of financial markets: Who trades ahead of major announcements? University of Texas working paper.

Gutierrez, Roberto C., and Eric K. Kelley, 2008, The long-lasting momentum in weekly returns, *Journal of Finance* 63, 415-447.

Hvidjkaer, Soeren, 2008, Small trades and the cross-section of stock returns, *Review of Financial Studies* 21, 1123-1151.

Kaniel, Ron, and Hong Liu, 2006, So what orders do informed traders use? *Journal of Business* 79, 1867-1913.

Kaniel, Ron, Gideon Saar, Sheridan Titman, 2008 , Individual investor sentiment and stock returns, *Journal of Finance* 63, 273-310.

Kaniel, Ron, Shuming Liu, Gideon Saar, Sheridan Titman, 2010, Individual investor trading and return patterns around earnings announcements, Duke University working paper.

Linnainmaa, Juhani T., 2010, Do limit orders alter inferences about investor performance and behavior? *Journal of Finance* 65, 1473-1506.

Loughran, Tim, and Bill McDonald, 2010, When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks, *Journal of Finance*, forthcoming.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703-708.

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775-1798.

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

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705-739.

Tetlock, Paul C., 2007, Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139-1168.

Tetlock, Paul C., Maytal Saar-Tsechansky, and Sofus Macskassy, 2008, More than words: Using language to quantify firms' fundamentals, *Journal of Finance* 63, 1437-1467.

Tetlock, Paul C., 2010a, All the news that's fit to reprint: Do investors react to stale information? *Review of Financial Studies*, forthcoming.

Tetlock, Paul C., 2010b, Does public financial news resolve asymmetric information? *Review of Financial Studies* 23, 3520-3557.

Table I: Cross-sectional Summary Statistics

This table presents time series averages of daily cross-sectional summary statistics. Panel A contains means, standard deviations and percentiles. Panel B contains average daily cross-sectional correlation coefficients. Retail imbalances computed from market, executed limit, and nonmarketable limit orders are represented by *MktImb*, *XLImb*, and *NmLImb*, respectively. Buys and sells are measured in numbers of shares ordered. Imbalances are defined as buys minus sells divided by buys plus sells; they are missing on stock-days in which fewer than 5 orders occurred. Other variables include daily stock returns (*Ret*), the fraction of words in Dow Jones news stories that appear in the list of Harvard-IV negative words (*RawH4Neg*), the fraction that appear in the list of financial negative words of Loughran and McDonald (2010), and a composite negativity measure (*RawNeg* = (1/3)**Raw H4Neg* + (2/3)**RawFinNeg*). The variable *Neg* is either *RawNeg* minus its daily mean or zero for stocks with no news coverage. The variables *H4Neg* and *FinNeg* are constructed analogously. The variables *ME* and *BM* are the natural logs of market equity from the most recent June and one plus the ratio of the most recent book equity to market equity from the most recent December. The notation [*x*,*y*] represents variables constructed from day $t + x$ through day $t + y$. All other variables are measured on day t (notation suppressed).

Panel A: Average daily statistics

Variable	*Mean*	*N*	*Std Dev*	*Pctl 5*	*Pctl 25*	*Pctl 50*	*Pctl 75*	*Pctl 95*
MktImb	-0.06554	2795	0.52726	-0.94022	-0.46618	-0.06521	0.31328	0.84575
NmLImb	-0.01372	2166	0.56676	-0.95150	-0.45332	-0.01504	0.41899	0.94190
XLImb	0.03100	1300	0.61024	-0.96068	-0.46748	0.04118	0.53974	0.98033
Ret	0.00133	2795	0.03299	-0.03863	-0.01140	0.00005	0.01206	0.04450
RawH4Neg	0.03136	780	0.02434	0.00145	0.01701	0.02723	0.03993	0.07812
RawFinNeg	0.01149	780	0.02238	0.00000	0.00024	0.00335	0.01218	0.05641
RawNeg	0.01811	780	0.02135	0.00060	0.00704	0.01227	0.02082	0.06010
Neg	0.00000	2795	0.01101	-0.01237	-0.00035	0.00000	0.00004	0.00705

Panel B: Average daily cross-sectional correlations

Variable	*NmLImb*	*XLImb*	*Neg*	*H4Neg*	*FinNeg*	*Neg*[-5,-1]	*Neg*[-26,-6]	*Ret*	*Ret*[-5,-1]	*Ret*[-1]	*Ret*[-26,-6]	*ME*	*BM*
MktImb	0.260	0.242	-0.010	-0.010	-0.009	-0.010	-0.010	0.059	-0.014	0.009	-0.022	-0.007	-0.020
NmLImb		0.777	-0.002	-0.004	-0.001	-0.007	-0.009	-0.128	-0.057	-0.039	-0.029	-0.048	0.004
XLImb			-0.003	-0.004	-0.002	-0.007	-0.008	-0.279	-0.040	-0.030	-0.020	-0.069	-0.003
Neg				0.861	0.958	0.094	0.083	-0.029	-0.010	-0.008	-0.013	0.120	-0.009
H4Neg					0.682	0.098	0.095	-0.025	-0.011	-0.008	-0.011	0.119	-0.011
FinNeg						0.081	0.066	-0.028	-0.008	-0.008	-0.012	0.108	-0.007
Neg[-5,-1]							0.154	-0.006	-0.031	-0.015	-0.017	0.125	-0.010

Table II: Predicting Returns Using Retail Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of future returns on retail imbalances and control variables. The independent variable *Imbalance*[0] measures day *t* retail imbalance constructed from either market (*Mkt*) or nonmarketable (*NmL*) orders and equals buys minus sells divided by buys plus sells. Buys and sells are measured in numbers of shares ordered, and at least 5 orders from the corresponding order type are required. The variable *Ret*[*x*,*y*] is the return compounded over days *t*+*x* through *t*+*y*. The variable *CAR*[*x*,*y*] is abnormal return summed from days *t*+*x* through *t*+*y* where each day's abnormal return is based on loadings from the Fama-French (1993) 3-factor model estimated over days *t*-257 through *t*-27 and contemporaneous factor realizations. The variables *MarketEquity* and *Book-to-Market* are the logs of market equity from the most recent June and one plus the ratio of book equity from the most recent fiscal year to market equity from the most recent December. Panel A uses *Ret*[*x*,*y*] from various horizons over days *t*+1 through *t*+20 as the dependent variable and either market or nonmarketable orders to measure imbalances. Panel B (Panel C) uses *CAR*[*x*,*y*] from horizons over days *t*+1 to *t*+60 as the dependent variable and market (nonmarketable) orders to measure imbalances. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Panel A: Market and nonmarketable imbalances predicting raw returns

Dependent Variable	*Ret*[1]	*Ret*[2,5]	*Ret*[6,10]	*Ret*[11,20]	*Ret*[1]	*Ret*[2,5]	*Ret*[6,10]	*Ret*[11,20]
Imbalance Measure	*Mkt*	*Mkt*	*Mkt*	*Mkt*	*NmL*	*NmL*	*NmL*	*NmL*
Imbalance[0]	0.098**	0.108**	0.071**	0.080**	0.088**	0.108**	0.066**	0.040*
	(0.004)	(0.010)	(0.012)	(0.019)	(0.005)	(0.011)	(0.012)	(0.016)
Ret[0]	-1.329**	-2.994**	-0.444	0.036	-1.286**	-2.716**	-0.223	0.336
	(0.200)	(0.363)	(0.336)	(0.513)	(0.196)	(0.356)	(0.329)	(0.487)
Ret[-5,-1]	-0.688**	-0.892**	-0.057	-0.092	-0.692**	-0.868**	-0.063	-0.042
	(0.090)	(0.242)	(0.255)	(0.433)	(0.092)	(0.245)	(0.259)	(0.430)
Ret[-26,-6]	-0.046	-0.175	-0.217	-0.258	-0.04	-0.155	-0.199	-0.249
	(0.042)	(0.140)	(0.157)	(0.311)	(0.043)	(0.143)	(0.156)	(0.307)
MarketEquity	-0.016**	-0.036*	-0.029	-0.045	-0.014**	-0.034*	-0.025	-0.043
	(0.004)	(0.017)	(0.020)	(0.047)	(0.004)	(0.017)	(0.019)	(0.046)
Book-to-Market	0.032*	0.065	0.058	0.176	0.044**	0.091	0.108	0.227
	(0.015)	(0.057)	(0.069)	(0.155)	(0.015)	(0.059)	(0.071)	(0.161)
Intercept	0.309**	0.812*	0.763*	1.258	0.270**	0.758*	0.675^{+}	1.176
	(0.069)	(0.315)	(0.372)	(0.887)	(0.069)	(0.314)	(0.370)	(0.891)
Average R^2	2.18%	2.15%	1.97%	2.05%	2.29%	2.23%	2.03%	2.08%
Average N	2691	2689	2686	2681	2080	2079	2077	2074

Table II (continued)

Panel B: Market imbalance predicting risk-adjusted returns

Dependent Variable	*CAR*[1]	*CAR*[2,5]	*CAR*[6,10]	*CAR*[11,20]	*CAR*[21,40]	*CAR*[41,60]
Imbalance Measure	*Mkt*	*Mkt*	*Mkt*	*Mkt*	*Mkt*	*Mkt*
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Imbalance[0]	0.097**	0.105**	0.068**	0.085**	0.072*	0.022
	(0.004)	(0.010)	(0.012)	(0.020)	(0.034)	(0.036)
Average R^2	1.81%	1.83%	1.71%	1.91%	2.28%	2.24%
Average N	2692	2689	2686	2681	2669	2656

Panel C: Nonmarketable imbalance predicting risk-adjusted returns

Dependent Variable	*CAR*[1]	*CAR*[2,5]	*CAR*[6,10]	*CAR*[11,20]	*CAR*[21,40]	*CAR*[41,60]
Imbalance Measure	*NmL*	*NmL*	*NmL*	*NmL*	*NmL*	*NmL*
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Imbalance[0]	0.092**	0.127**	0.091**	0.110**	0.135**	0.116**
	(0.005)	(0.012)	(0.012)	(0.017)	(0.031)	(0.039)
Average R^2	1.95%	1.98%	1.86%	2.03%	2.35%	2.33%
Average N	2080	2079	2077	2074	2066	2057

Table III: Predicting Negativity Using Retail Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of future negativity on retail imbalances and control variables. The dependent variable *Neg*[*x*,*y*] is the fraction of words in Dow Jones news stories from day *t* + *x* through day *t* + *y* that appear in the list of Harvard-IV negative words (*RawH4Neg*) and the fraction that appear in the list of financial negative words of Loughran and McDonald (2010), using weights of (1/3) and (2/3), respectively. This variable is constructed to have a zero mean and to be zero for stocks with no news coverage. Other variables are as defined above. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable Imbalance Measure	*Neg*[1] *Mkt*	*Neg*[2,5] *Mkt*	*Neg*[6,10] *Mkt*	*Neg*[11,20] *Mkt*	*Neg*[1] *NmL*	*Neg*[2,5] *NmL*	*Neg*[6,10] *NmL*	*Neg*[11,20] *NmL*
Imbalance[0]	-0.010**	-0.007**	-0.008**	-0.007**	-0.002^{+}	0.003	-0.001	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Neg[0]	8.555**	6.975**	5.818**	4.531**	8.411**	6.713**	5.483**	4.192**
	(0.162)	(0.165)	(0.159)	(0.117)	(0.172)	(0.162)	(0.167)	(0.118)
Neg[-5,-1]	5.798**	8.639**	8.524**	8.273**	6.085**	8.979**	8.699**	8.278**
	(0.141)	(0.222)	(0.212)	(0.236)	(0.154)	(0.244)	(0.226)	(0.241)
Neg[-26,-6]	8.297**	16.654**	18.374**	22.194**	8.657**	17.214**	18.900**	23.010**
	(0.188)	(0.529)	(0.603)	(0.896)	(0.199)	(0.513)	(0.595)	(0.921)
Ret[0]	-0.128**	-0.051^{+}	-0.087**	0.009	-0.167**	-0.084**	-0.116**	-0.024
	(0.026)	(0.028)	(0.027)	(0.024)	(0.026)	(0.027)	(0.027)	(0.021)
Ret[-5,-1]	-0.035**	-0.067**	-0.021	-0.011	-0.044**	-0.078**	-0.025	-0.025
	(0.010)	(0.018)	(0.022)	(0.023)	(0.011)	(0.018)	(0.021)	(0.023)
Ret[-26,-6]	-0.015**	-0.011	-0.004	-0.031*	-0.021**	-0.013	-0.010	-0.031*
	(0.005)	(0.012)	(0.014)	(0.015)	(0.006)	(0.011)	(0.013)	(0.015)
MarketEquity	0.065**	0.071**	0.068**	0.054**	0.065**	0.070**	0.067**	0.055**
	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)
Book-to-Market	0.029**	0.034**	0.029**	0.015	0.047**	0.043**	0.038**	0.015
	(0.003)	(0.006)	(0.007)	(0.010)	(0.003)	(0.007)	(0.008)	(0.010)
Intercept	-0.897**	-0.971**	-0.935**	-0.746**	-0.884**	-0.954**	-0.919**	-0.744**
	(0.020)	(0.034)	(0.037)	(0.040)	(0.019)	(0.032)	(0.035)	(0.040)
Average R^2	4.03%	5.22%	5.45%	6.83%	4.30%	5.80%	6.03%	7.64%
Average N	2692	2692	2692	2692	2081	2081	2081	2081

Table IV: Predicting Analysts' Earnings Forecast Errors Using Retail Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of earnings forecast errors on retail imbalances and control variables. The dependent variable *SignFE*[*x*,*y*] is the sign of analyst forecast errors for quarterly earnings announcements occurring from day *t* + *x* through day *t* + *y* and zero if there is no earnings announcement. The forecast error is the difference between actual earnings-per-share and the median analyst forecast from I/B/E/S. Other variables are as defined above. At least 30 earnings announcements with corresponding forecast data during the window of the dependent are required for each daily cross-sectional regression. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	*SignFE*[1]	*SignFE*[2,5]	*SignFE*[6,10]	*SignFE*[11,20]	*SignFE*[1]	*SignFE*[2,5]	*SignFE*[6,10]	*SignFE*[11,20]
Imbalance Measure	*Mkt*	*Mkt*	*Mkt*	*Mkt*	*NmL*	*NmL*	*NmL*	*NmL*
Imbalance[0]	0.389**	0.239**	0.063	0.089	0.286**	0.086	-0.002	-0.186**
	(0.035)	(0.039)	(0.036)	(0.049)	(0.038)	(0.047)	(0.041)	(0.061)
Neg[0]	1.459	-5.905**	-7.244**	-13.212**	1.732	-7.983**	-7.145**	-14.182**
	(1.733)	(2.123)	(1.977)	(2.857)	(2.122)	(2.592)	(2.311)	(2.973)
Neg[-5,-1]	-8.611**	-16.451**	-16.646**	-17.445**	-10.11**	-19.819**	-18.951**	-19.411**
	(1.779)	(2.806)	(3.134)	(3.832)	(2.146)	(3.270)	(3.523)	(3.928)
Neg[-26,-6]	-16.341**	-33.746**	-31.133**	-47.695**	-15.854**	-34.900**	-32.442**	-50.589**
	(1.976)	(3.026)	(3.646)	(7.153)	(2.352)	(3.958)	(5.083)	(8.151)
Ret[0]	2.351**	2.947**	3.953**	5.950**	3.188**	3.696**	4.353**	5.619**
	(0.435)	(0.607)	(0.625)	(0.911)	(0.481)	(0.671)	(0.667)	(0.899)
Ret[-5,-1]	1.827**	3.668**	3.420**	5.620**	1.867**	3.923**	3.585**	5.225**
	(0.248)	(0.509)	(0.560)	(0.851)	(0.264)	(0.522)	(0.617)	(0.785)
Ret[-26,-6]	1.603**	2.978**	2.839**	3.813**	1.567**	3.095**	3.039**	3.576**
	(0.151)	(0.348)	(0.390)	(0.598)	(0.172)	(0.356)	(0.388)	(0.587)
MarketEquity	0.348**	0.722**	0.805**	1.284**	0.379**	0.799**	0.898**	1.282**
	(0.021)	(0.068)	(0.083)	(0.141)	(0.023)	(0.069)	(0.084)	(0.134)
Book-to-Market	-0.197**	-0.479**	-0.469**	-0.832**	-0.207*	-0.559**	-0.535**	-0.834**
	(0.066)	(0.113)	(0.126)	(0.219)	(0.087)	(0.142)	(0.160)	(0.234)
Intercept	-3.662**	-7.681**	-8.62**	-13.593**	-3.969**	-8.503**	-9.578**	-13.561**
	(0.242)	(0.753)	(0.912)	(1.528)	(0.265)	(0.757)	(0.920)	(1.444)
Days	362	815	932	1181	314	695	778	1145
Average R^2	0.51%	0.74%	0.78%	0.99%	0.62%	0.96%	1.01%	1.19%
Average N	2781	2739	2739	2701	2159	2112	2122	2089

Table V: Predicting Returns Using Retail Order Imbalances and Quoted Spreads

This table presents results from daily Fama-MacBeth (1973) regressions of future returns on retail imbalances and interactions based on bid-ask spreads. For each stock-day and order type, we compute a share-weighted average percentage spread using the NBBOs at the time of order submission. The variable *SpreadQuint* equals -2, -1, 0, 1, or 2 corresponding to the quintile rank of a stock's average spread. In order to be ranked on day *t*, a firm must have at least five orders. All other firms have *SpreadQuint* set to 0 for that day. The variable *SizeQuint* equals -2, -1, 0, 1, or 2 corresponding to the firm's NYSE market value quintile as of the prior June. Other variables are defined as above. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	*Ret*[1]	*Ret*[2,5]	*Ret*[6,10]	*Ret*[11,20]	*Ret*[1]	*Ret*[2,5]	*Ret*[6,10]	*Ret*[11,20]
Imbalance Measure	*Mkt*	*Mkt*	*Mkt*	*Mkt*	*NmL*	*NmL*	*NmL*	*NmL*
Imbalance[0]	0.079**	0.088**	0.051**	0.076**	0.078**	0.100**	0.070**	0.059**
	(0.005)	(0.012)	(0.016)	(0.023)	(0.005)	(0.011)	(0.012)	(0.016)
Imb[0]**SpreadQuint*	0.014**	0.024**	-0.008	0.001	0.032**	0.060**	0.047**	0.045**
	(0.004)	(0.009)	(0.011)	(0.016)	(0.004)	(0.009)	(0.011)	(0.016)
Imb[0]**SizeQuint*	-0.022**	-0.025**	-0.023*	-0.007	-0.014**	-0.013^{+}	0.003	0.018
	(0.004)	(0.008)	(0.010)	(0.014)	(0.004)	(0.008)	(0.009)	(0.013)
Ret[0]*S*preadQuint*	-0.450**	-0.969**	-0.322^{+}	-0.388	-0.787**	-1.031**	-0.258	-0.123
	(0.111)	(0.185)	(0.188)	(0.286)	(0.121)	(0.198)	(0.202)	(0.293)
SpreadQuint	0.009*	0.020	0.023	0.057	0.004	0.010	0.022	0.039
	(0.005)	(0.017)	(0.022)	(0.047)	(0.005)	(0.017)	(0.020)	(0.046)
Ret[0]	-1.129**	-2.393**	-0.193	0.284	-0.807**	-2.001**	0.010	0.437
	(0.223)	(0.402)	(0.379)	(0.571)	(0.214)	(0.385)	(0.360)	(0.548)
Ret[-5,-1]	-0.685**	-0.906**	-0.079	-0.083	-0.687**	-0.870**	-0.052	-0.027
	(0.090)	(0.239)	(0.255)	(0.421)	(0.092)	(0.243)	(0.261)	(0.420)
Ret[-26,-6]	-0.045	-0.175	-0.216	-0.241	-0.038	-0.152	-0.194	-0.227
	(0.041)	(0.137)	(0.155)	(0.304)	(0.043)	(0.141)	(0.154)	(0.301)
Market Equity	-0.013**	-0.030*	-0.018	-0.015	-0.013**	-0.031*	-0.012	-0.020
	(0.004)	(0.014)	(0.017)	(0.035)	(0.004)	(0.014)	(0.017)	(0.035)
Book-to-Market	0.030*	0.059	0.054	0.170	0.043**	0.085	0.102	0.218
	(0.014)	(0.057)	(0.071)	(0.154)	(0.015)	(0.059)	(0.072)	(0.162)
Intercept	0.273**	0.738**	0.637*	0.871	0.247**	0.717**	0.518	0.896
	(0.063)	(0.261)	(0.318)	(0.693)	(0.066)	(0.269)	(0.334)	(0.718)
Average R^2	2.64%	2.54%	2.34%	2.44%	2.76%	2.63%	2.41%	2.49%
Average N	2691	2689	2686	2681	2080	2079	2077	2074

Table VI: Predicting Next-Day Retail Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of day t + 1 retail imbalances based on market (*Mkt*), nonmarketable (*NmL*), or executed limit (*XL*) orders on prior imbalances, negativity, and returns. The variable *Earn*[-1,0] is one if an earnings announcement occurred and zero otherwise; for specifications involving *Earn*, at least 30 announcements are required for each cross-sectional regression. Other variables are as defined above. Average coefficients and Newey-West (1987) standard errors with 60 lags appear in the table. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Imbalance Variable	*Mkt*	*Mkt*	*NmL*	*NmL*	*XL*	*XL*
Imbalance[0]	0.144**	0.146**	0.208**	0.206**	0.171**	0.168**
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)
Imbalance[-5,-1]	0.190**	0.192**	0.164**	0.165**	0.138**	0.138**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Imbalance[-26,-6]	0.225**	0.220**	0.124**	0.123**	0.111**	0.108**
	(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
Neg[0]	-0.253**	-0.221**	-0.050	-0.056	-0.016	0.040
	(0.025)	(0.032)	(0.051)	(0.063)	(0.062)	(0.081)
Neg[-5,-1]	-0.270**	-0.270**	-0.086*	-0.068	-0.067	-0.072
	(0.032)	(0.030)	(0.036)	(0.043)	(0.046)	(0.055)
Neg[-26,-6]	-0.425**	-0.411**	-0.135**	-0.149**	-0.054	-0.113
	(0.059)	(0.071)	(0.051)	(0.054)	(0.082)	(0.079)
Ret[0]	0.092**	0.081	-0.325**	-0.327**	0.486**	0.466**
	(0.036)	(0.048)	(0.084)	(0.096)	(0.070)	(0.091)
Ret[-5,-1]	-0.211**	-0.220**	-0.184**	-0.188**	-0.020	-0.027
	(0.010)	(0.013)	(0.016)	(0.019)	(0.017)	(0.018)
Ret[-26,-6]	-0.058**	-0.060**	-0.029**	-0.033**	0.002	0.001
	(0.006)	(0.007)	(0.007)	(0.009)	(0.007)	(0.009)
News[0]	-0.002	0.000	-0.004**	-0.002	0.001	0.004
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
News[0]**Imb*[0]	0.011**	0.009**	-0.02**	-0.022**	-0.032**	-0.030**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
News[0]**Ret*[0]	-0.143**	-0.117**	0.141*	0.156**	-0.418**	-0.277**
	(0.019)	(0.025)	(0.058)	(0.058)	(0.057)	(0.051)
Earn[-1,0]		-0.028**		-0.024**		-0.015
		(0.005)		(0.005)		(0.008)
Earn[-1,0]**Imb*[0]		-0.022**		-0.029**		-0.046**
		(0.006)		(0.007)		(0.009)
Earn[-1,0]**Ret*[0]		-0.234**		0.066		-0.695**
		(0.031)		(0.109)		(0.110)
SignFE[-1,0]		-0.014**		-0.034**		-0.039**
		(0.004)		(0.007)		(0.007)
MarketEquity	0.003**	0.003*	-0.005**	-0.005**	-0.013**	-0.014**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-Market	-0.019**	-0.019**	-0.011**	-0.011**	-0.020**	-0.021**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.004)	(0.006)
Intercept	-0.070**	-0.072**	0.058**	0.061**	0.205**	0.222**
	(0.012)	(0.015)	(0.007)	(0.009)	(0.012)	(0.016)
Average R^2	7.87%	7.99%	8.79%	8.93%	7.04%	7.27%
Average N	2647	2712	2015	2033	1185	1197

Table VII: Retail Order Imbalances and Intraday Returns

This table summarizes intraday returns over various horizons for 6 order types: market (*Mkt*), marketable limit (*MktL*), nonmarketable limits priced within 10 cents of the inside quote (*NmL-near*), nonmarketable limits not priced within 10 cents of the inside quote (*NmL-far*), executed limits priced within 10 cents of the inside quote (*XL-near*), and executed limits not priced within 10 cents of the inside quote (*XL-far).* The variable *RetPreO* is the return from the prior day closing quote midpoint to the midpoint of the best quote when the order is submitted. The variable *RetPostO* is the return from the midpoint of the best quote when the order is submitted to the midpoint of the current day's closing quote. The variable *HSpread* is the half spread in percentage terms based on the best quote when the order is submitted. For market and marketable limit orders, it assumes execution at the quote; for nonmarketable limits, it assumes execution at the limit price. The variable *RetPostX* is the return from the assumed execution price to the midpoint of the current day's closing quote. Other details on variable construction are discussed in the text. For each order type and stock-day, we take a weighted average of each return where the weights are the signed quantity of the order. We average across stocks for each day *t* and report the time series means. Numbers are in basis points.

Order Type	*Mkt*	*MktL*	*NmL-near*	*NmL-far*	*XL-near*	*XL-far*
RetPreO	10.57	-17.70	-48.23	-35.18	-47.21	-75.78
RetPostO	8.27	14.60	13.01	1.54	-23.28	-136.38
HSpread	16.32	15.95			-20.93	-131.82
RetPostX	-8.06	-1.36			-2.32	-4.69
Average N	2171	1187	1572	902	1060	167

Table VIII: Predicting Returns Using Persistent Retail Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of future returns on retail imbalances and interactions describing the expected persistence of *Imbalance*[0]. To estimate persistence, each day *t* we rank firms according to their market imbalance autocorrelation coefficients obtained from a model using the most recent 63 days of daily data. The variable *Persist* equals -2, -1, 0, 1, or 2 corresponding to the quintile rank of the autocorrelation coefficient. In order to be ranked on day *t*, a firm must have daily imbalance data from at least 90% of the available trading days in the ranking period, and its autocorrelation coefficient must be between -1 and 1. All other firms have *Persist* set to 0 for that day. Other variables are defined as above. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	*Ret*[1,5]	*Ret*[6,10]	*Ret*[11,20]	*Ret*[1,5]	*Ret*[6,10]	*Ret*[11,20]
Imbalance measure	*Mkt*	*Mkt*	*Mkt*	*NmL*	*NmL*	*NmL*
Imbalance[0]	0.142**	0.054**	0.072**	0.108**	0.039**	0.030*
	(0.013)	(0.013)	(0.021)	(0.012)	(0.011)	(0.013)
Persist	-0.005	-0.007	-0.002	-0.007	-0.005	0.001
	(0.006)	(0.006)	(0.012)	(0.008)	(0.007)	(0.014)
Imb[0]**Persist*	0.020**	0.004	-0.006	0.012	0.002	0.001
	(0.006)	(0.007)	(0.012)	(0.008)	(0.006)	(0.010)
Imb[0]**SizeQuint*	-0.075**	-0.019*	-0.010	-0.101**	-0.032**	-0.014
	(0.008)	(0.007)	(0.011)	(0.007)	(0.006)	(0.011)
Ret[0]**Persist*	0.072	-0.167	-0.050	0.094	-0.101	-0.034
	(0.182)	(0.155)	(0.182)	(0.199)	(0.163)	(0.195)
Ret[0]	-4.473**	-0.448	-0.001	-3.962**	-0.182	0.312
	(0.409)	(0.341)	(0.514)	(0.406)	(0.333)	(0.491)
Ret[-5,-1]	-1.592**	-0.061	-0.095	-1.550**	-0.060	-0.039
	(0.300)	(0.259)	(0.433)	(0.306)	(0.264)	(0.430)
Ret[-26,-6]	-0.233	-0.217	-0.253	-0.200	-0.197	-0.244
	(0.171)	(0.159)	(0.311)	(0.177)	(0.157)	(0.306)
Market Equity	-0.055*	-0.030	-0.046	-0.050*	-0.025	-0.043
	(0.023)	(0.021)	(0.047)	(0.022)	(0.020)	(0.046)
Book-to-Market	0.096	0.057	0.174	0.134	0.108	0.225
	(0.073)	(0.071)	(0.154)	(0.075)	(0.072)	(0.161)
Intercept	1.158**	0.780*	1.261	1.045*	0.680	1.178
	(0.415)	(0.389)	(0.884)	(0.413)	(0.387)	(0.892)
Average R^2	2.54%	2.18%	2.24%	2.68%	2.27%	2.31%
Average N	2689	2686	2681	2079	2077	2074

Table IX: Predicting Returns Using the Extent of Broker Internalization

This table presents results from daily Fama-MacBeth (1973) regressions of future returns on retail order imbalances and interactions describing the extent to which brokers internalize order flow using data from a subset of brokers in the main dataset. For each stock-day and order type, the variable *InternRatio* is the ratio of flow internalized to flow routed to our market centers by this subset of brokers in the preceding month. We use this ratio to construct four variables. The variable *IntDum* is one when *InternRatio* is positive and zero otherwise. For observations with *IntDum* equal one, the variable *IntQuint* equals -2, -1, 0, 1, or 2 corresponding to the quintile rank of *InternRatio* for that month. For observations with *IntDum* equal zero, *IntQuint* is set to 0. Other variables are defined as above. The *Imbalance*[0] calculations require at least 2 orders of the corresponding order type, and each cross-sectional regression requires at least 100 observations. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	*Ret*[1,5]	*Ret*[6,10]	*Ret*[11,20]	*Ret*[1,5]	*Ret*[6,10]	*Ret*[11,20]
Imbalance Measure	*Mkt*	*Mkt*	*Mkt*	*NmL*	*NmL*	*NmL*
Imbalance[0]	0.114**	0.047**	0.024	0.094**	0.037**	0.080**
	(0.014)	(0.014)	(0.024)	(0.014)	(0.013)	(0.019)
Imb[0]**IntDum*	-0.048*	-0.018	0.031	-0.046*	0.007	-0.071*
	(0.021)	(0.019)	(0.027)	(0.020)	(0.020)	(0.028)
Imb[0]**IntQuint*	-0.015^{+}	-0.007	-0.021^{+}	-0.003	-0.025**	-0.008
	(0.008)	(0.008)	(0.011)	(0.009)	(0.009)	(0.012)
IntDum	-0.067	-0.075	-0.121	-0.135^{+}	-0.116^{+}	-0.219
	(0.068)	(0.066)	(0.132)	(0.069)	(0.068)	(0.135)
IntQuint	-0.004	-0.005	-0.016	0.006	0.009	0.009
	(0.014)	(0.013)	(0.026)	(0.015)	(0.014)	(0.029)
Imb[0]**SizeQuint*	-0.032**	-0.022**	-0.013^{+}	-0.059**	-0.015*	-0.014
	(0.005)	(0.006)	(0.008)	(0.007)	(0.007)	(0.010)
Ret[0]	-4.832**	-0.523	-0.138	-4.415**	-0.207	0.192
	(0.399)	(0.327)	(0.485)	(0.413)	(0.318)	(0.483)
Ret[-5,-1]	-1.714**	-0.090	-0.139	-1.677**	-0.074	-0.192
	(0.299)	(0.257)	(0.406)	(0.306)	(0.264)	(0.410)
Ret[-26,-6]	-0.238	-0.221	-0.261	-0.258	-0.212	-0.280
	(0.168)	(0.149)	(0.296)	(0.170)	(0.152)	(0.297)
MarketEquity	-0.049^{+}	-0.026	-0.046	-0.043	-0.021	-0.032
	(0.027)	(0.025)	(0.056)	(0.027)	(0.025)	(0.056)
Book-to-Market	0.085	0.066	0.195	0.122	0.121^{+}	0.267^{+}
	(0.073)	(0.068)	(0.149)	(0.077)	(0.073)	(0.161)
Intercept	1.109*	0.779+	1.328	1.036*	0.694	1.137
	(0.448)	(0.414)	(0.958)	(0.451)	(0.425)	(0.972)
Average R^2	2.79%	2.47%	2.57%	2.93%	2.58%	2.64%
Average N	2479	2476	2471	1846	1844	1841

Table X: Predicting Returns Using Executed Limit Order Imbalances

This table presents results from daily Fama-MacBeth (1973) regressions of future Fama-French (1993) cumulative abnormal returns on retail executed limit order imbalances (*XL*) and control variables. Variables are defined as above. Average coefficients and Newey-West (1987) standard errors with lags equal to twice the horizon of the dependent variable appear in the table. Numbers are multiplied by 100. The symbols **, *, and $^{+}$ denote significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable	*CAR*[1]	*CAR*[2,5]	*CAR*[6,10]	*CAR*[11,20]	*CAR*[21,40]	*CAR*[41,60]
Imbalance Measure	*XL*	*XL*	*XL*	*XL*	*XL*	*XL*
Imbalance[0]	-0.018**	0.056**	0.047**	0.034	0.059	0.025
	(0.007)	(0.014)	(0.016)	(0.025)	(0.043)	(0.046)
Ret[0]	-0.670**	-2.166**	0.492	0.800^{+}	1.412*	0.857
	(0.223)	(0.367)	(0.329)	(0.448)	(0.720)	(0.765)
Ret[-5,-1]	-0.691**	-0.485^{+}	-0.056	0.346	0.501	-0.039
	(0.096)	(0.253)	(0.285)	(0.398)	(0.709)	(0.707)
Ret[-26,-6]	-0.056	-0.281*	-0.315*	-0.487	-0.570	-0.630
	(0.045)	(0.138)	(0.154)	(0.316)	(0.593)	(0.589)
MarketEquity	0.006	0.066**	0.089**	0.202**	0.406**	0.450**
	(0.004)	(0.018)	(0.021)	(0.050)	(0.112)	(0.106)
Book-to-Market	0.023	0.057	0.097	0.129	0.235	0.158
	(0.017)	(0.058)	(0.066)	(0.134)	(0.265)	(0.264)
Intercept	-0.107	-1.099**	-1.484**	-3.311**	-6.559**	-7.270**
	(0.066)	(0.275)	(0.323)	(0.769)	(1.731)	(1.643)
Average R^2	2.85%	2.76%	2.61%	2.78%	3.11%	3.13%
Average N	1249	1249	1248	1246	1242	1237

Figure 1: Predicting Returns and News Negativity Using Retail Order Imbalances.

Each bar in the figure represents a standardized predictability coefficient on retail order imbalances on day [0] from a different regression. The dependent variable in the regression is either raw returns or news negativity during days [1], [2,5], [6,10], or [11,20]. The independent imbalance variable is based on either retail market orders (*MktImb*) or retail nonmarketable limit orders (*NmLImb*). Regression coefficients are standardized by multiplying the coefficient by the 5th-to-95th percentile range for the independent variable and dividing by the 5th-to-95th percentile range of the daily version of the dependent variable.

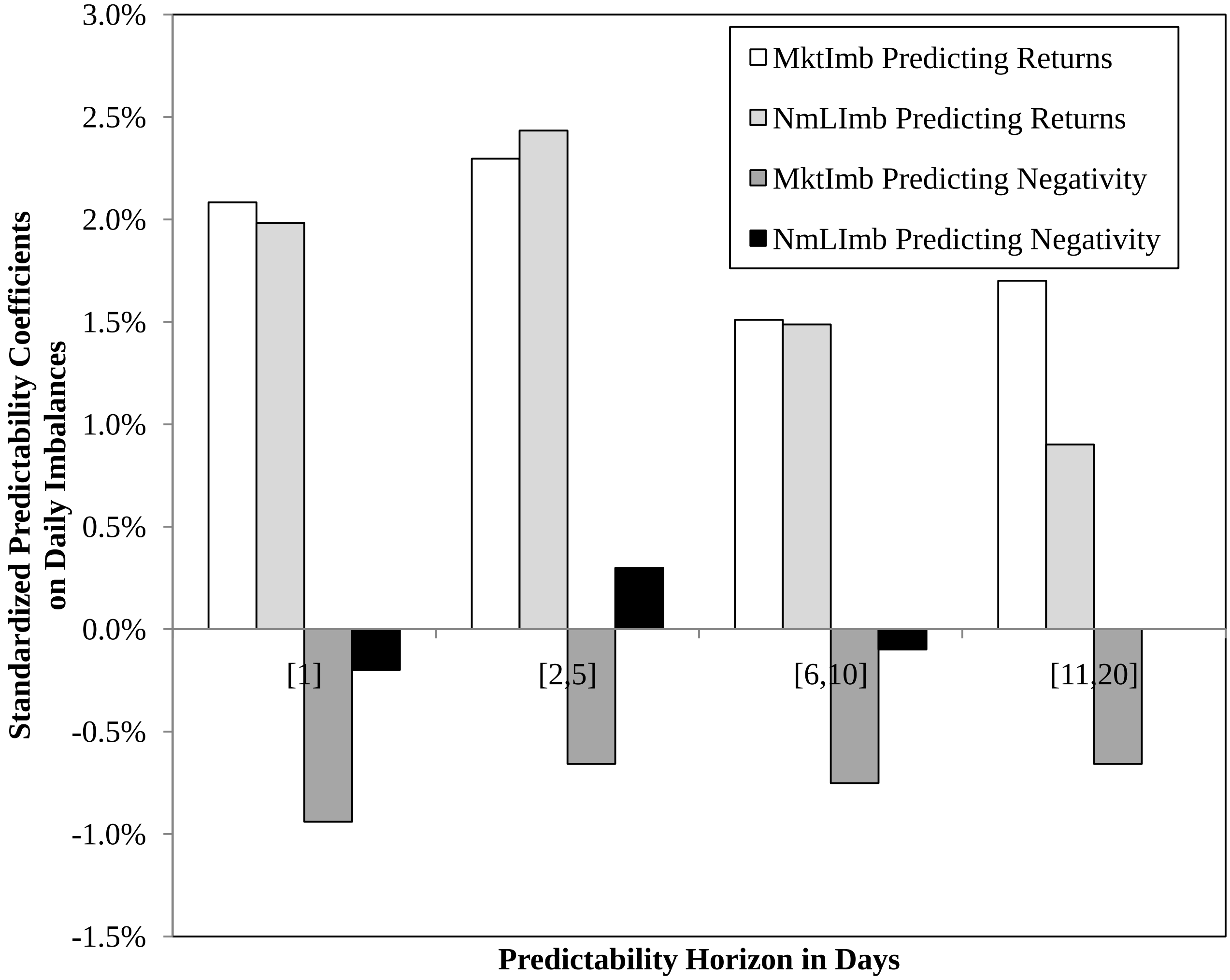

Figure 2, Panel A: Intraday Returns Before and After Order Submission

We plot cumulative intraday returns for market (*Mkt*) and near marketable limit (*NmL*) orders described in Table VII as *RetPreO* and *RetPostO*. Returns are normalized so that the cumulative return at the time of order submission equals zero.

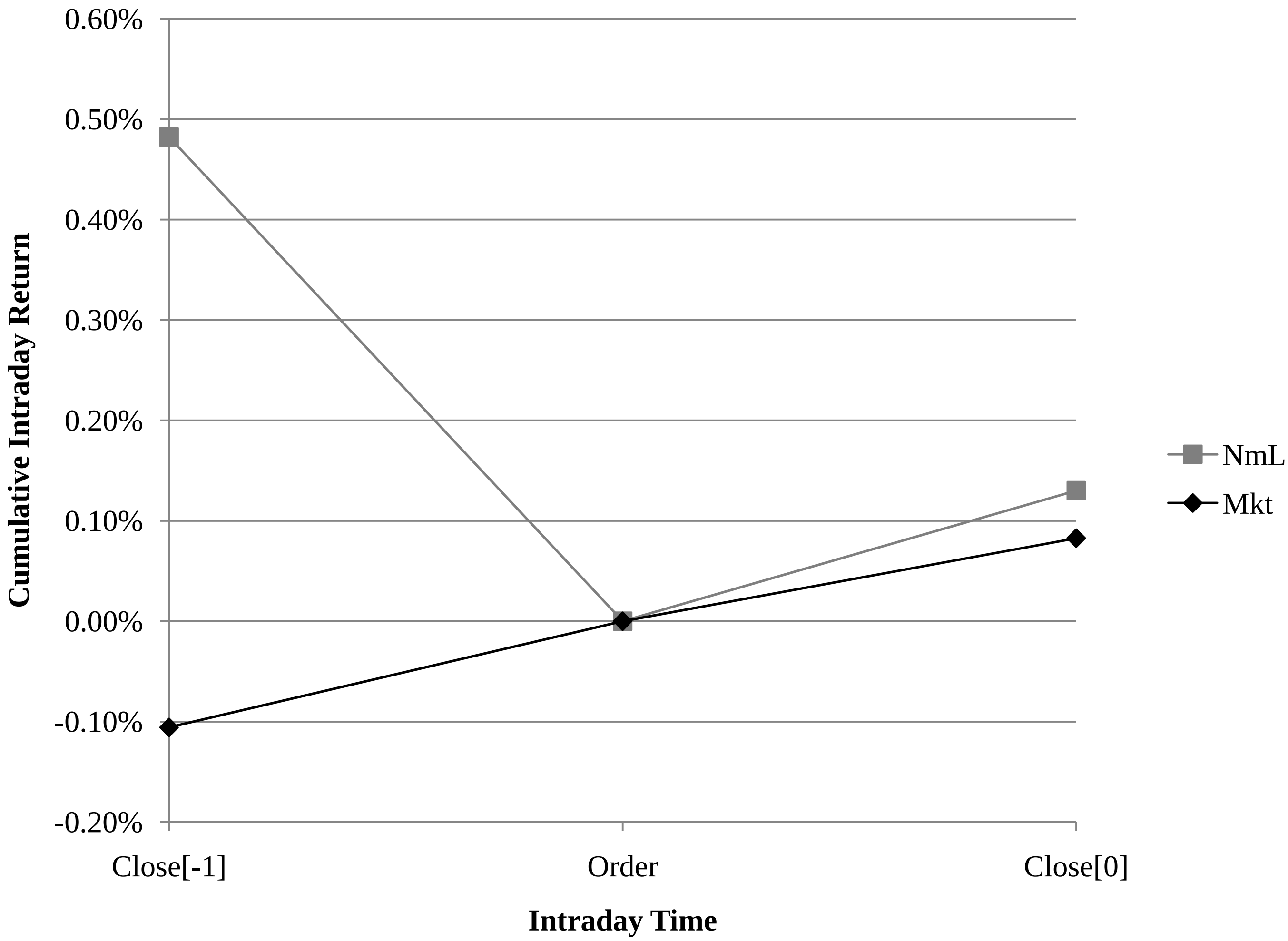

Figure 2, Panel B: Cumulative Alphas for Portfolios Based on Daily Retail Order Imbalances

Each day *t*, we sort firms into deciles based on retail order imbalances using either market (*Mkt*) or non-marketable limit (*NmL*) orders and form equal-weighted portfolios. For each event day from *t*-1 to *t*+5we compute Fama-French (1993) 3-factor alphas for a spread portfolio that is long stocks from the highest imbalance decile and short stocks from the lowest imbalance decile. Alphas are cumulated across event days and normalized such that cumulative alpha after event day t (the formation day) is zero.