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Order dynamics: Recent evidence from the NYSE

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Abstract

We examine investor order choices using evidence from a recent period when the NYSE trades in decimals and allows automatic executions. We analyze the decision to submit or cancel an order or to take no action. For submitted orders, we distinguish order type (market vs. limit), order side (buy vs. sell), execution method (auction vs. automatic), and pricing aggressiveness. We find that the NYSE exhibits positive serial correlation in order type on an order-by-order basis, which suggests that follow-on order strategies dominate adverse selection or liquidity considerations at a moment in time. Aggregated levels of order flow also exhibit positive serial correlation in order type, but appear to be non-stationary processes. Overall, changes in aggregated order flow have an order-type serial correlation that is close to zero at short aggregation intervals, but becomes increasingly negative at longer intervals. This implies a liquidity exhaustion–replenishment cycle. We find that small orders routed to the NYSE's floor auction process are sensitive to the quoted spread, but that small orders routed to the automatic execution system are not. Thus, in addition to foregoing price improvement, traders selecting the speed of automatic executions on the NYSE do so with little regard for the quoted cost of immediacy. As quoted depth increases, traders respond by competing on price via limit orders that undercut existing bid and ask prices. Limit orders are more likely and market sells are less likely late in the trading day. These results are helpful in understanding the order arrival process at the NYSE and have potential applications in academics and industry for optimizing order submission strategies.

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Order choice is important as it is the foundation of how security markets operate. Order submissions and cancellations determine the supply of and demand for liquidity. On a traditional exchange, such as the New York Stock Exchange (NYSE), specialists and floor brokers provide liquidity, but public orders play a major role. For example, Kavajecz (1999) finds that public limit orders are represented in 64% of NYSE specialists' quotes. Recent NYSE initiatives, such as decimals, Direct+, OpenBook, and Hybrid increase public limit orders' importance. If we can better understand the market conditions under which traders demand liquidity and those under which (and at what prices) they supply liquidity, then we can better understand the price formation process — markets' most important role. In addition, order choice affects execution quality, which is important to both consumers and regulators (for example, see United States Securities and Exchange Commission, 2001b).

The literature examining a trader's optimal order choice focuses on liquidity cycles, adverse selection problems, momentum-based trading strategies and order splitting. For example, Parlour (1998) finds that an order increasing the limit order book's depth, is more likely to follow an order decreasing depth on that side of the market than it is to follow any other order type. That is, a limit buy (sell) order is most likely to follow a market sell (buy). Thus, she predicts a liquidity exhaustion–replenishment cycle; what we define as negative serial correlation in order flow. Kaniel and Liu (2005) consider adverse selection in solving the informed investor's problem in a market with patient and impatient uninformed investors and a competitive market maker. Their model suggests that order flow is serially uncorrelated. Biais et al. (1995) suggest that traders might split large orders, follow what other traders are doing ("piggyback"), or react similarly to the same events. Yeo (2002) suggests that if a new limit order undercuts an old limit order price, then the old limit order might be cancelled and resubmitted at a better price. We refer to the Biais et al. and Yeo order strategies as "follow-on" order strategies and they imply positive serial correlation in order flow.

We use NYSE system order data from the era of decimal prices and automatic executions to estimate a multinomial logit model of order choice. Consistent with Biais et al. (1995) on the Paris Bourse and Griffiths et al. (1998) on the Toronto Stock Exchange, we find that the NYSE exhibits positive serial correlation in order type on an order-by-order basis. This suggests that follow-on order strategies dominate adverse selection or liquidity considerations at a moment in time. As it is possible that immediate effects and longer-run effects differ, we aggregate order flow over clock-time intervals ranging from five seconds to five minutes. Aggregated levels of order flow also exhibit positive serial order-type correlation, but seem to be non-stationary processes. Using standard ARIMA methodology, we first difference these time series. Overall, aggregated order flow changes have an order-type serial correlation that starts close to zero at short aggregation intervals, but becomes negative at longer intervals. Negative autocorrelation in order flow implies a liquidity exhaustion–replenishment cycle consistent with Parlour's model. Not surprisingly, we find that the exact relationship between serial correlation in order type and the length of the aggregation period depends on trading volume.

Employing data from a period of time where the NYSE allows automatic executions is particularly relevant as the NYSE rolls-out the Hybrid Market and contemplates a merger with the all-electronic Euronext Exchange (see Wall Street Journal, 2006). We find that small orders routed to the NYSE's floor auction process are sensitive to the quoted spread, but that small orders routed to the automatic execution system are not. Thus, in addition to foregoing price improvement, traders selecting the speed of automatic executions on the NYSE do so with little regard for the quoted cost of immediacy. Our results complement the speed versus cost trade-off documented in Boehmer (2005).

We have several other findings. Late in the trading day, limit orders are more likely and market sells are less likely. This is consistent with experimental evidence in Bloomfield et al. (2005) that informed traders switch from demanding liquidity early in the day to providing liquidity later. These results complement Anand et al. (2005) who find that NYSE limit orders are more profitable early in the day and that informed market orders drive more price discovery in the morning than in the afternoon. We also document that traders are more likely to "jump the queue" by submitting limit orders with prices improving existing quotes and less likely to submit orders with prices worse than current quotes when the quoted depth is large. We find that order activity is clustered and that doing nothing, defined as time passing without order activity, is clustered. Consistently with previous work, we find that narrower (wider) spreads increase the probability of marketable (limit) orders. However, we document that this effect is limited primarily to small orders, which are likely to be within quoted size, and affects marketable limit orders more strongly than market orders.

We study a wide spectrum of choices including order type (market vs. limit), order side (buy vs. sell), order pricing aggressiveness (executable vs. limit prices better than, equal to, or worse than the current quote), order cancellation, execution method (automatic vs. auction), and the fundamental choice between order activity and doing nothing. Our work complements prior work on order choice examining markets with an open limit order book (Biais et al., 1995; Hall and Hautsch, 2004), NASDAQ (Smith, 2000), and 1990–1991 NYSE using the TORQ dataset (Bae et al., 2003; Beber and Caglio, 2002; Wald and Horrigan, 2005; Anand et al., 2005).

The paper is organized as follows. Section 1 presents a literature review and states our hypotheses. Section 2 describes the data we obtain from the NYSE. Section 3 explains our empirical methodology. Section 4 presents our results. Section 5 concludes.

1. Literature review and hypotheses

1.1. Order-by-order serial correlation in order type

Parlour (1998) models an open-limit-order-book market in which traders arrive sequentially and choose whether to submit a market order or a limit order. The optimal order choice depends on the trader's degree of patience and on the current state of the limit order book. If the prior trader submitted a limit buy (limit sell) order, then the bid depth (ask depth) increased. This makes it relatively less attractive for the current trader to submit another limit buy (limit sell). That is, Parlour predicts what we call negative serial correlation in limit order type (her Proposition V); observing consecutive limit buy (limit sell) orders is less likely than observing any other pair of orders.

Kaniel and Liu (2005) incorporate private information into a model of optimal order choice. Their model randomly draws from four types of uninformed traders (impatient buyers who submit market buys, impatient sellers who submit market sells, patient buyers who submit limit buys, patient sellers who submit limit sells) and informed traders who strategically make the buy–sell and market-limit choice. After each trade in their model, the market maker sets bid and asks prices to make informed buy and sell orders equally likely based on the market maker's information. The market maker's quoted prices also make the informed trader indifferent between providing and demanding liquidity. Thus, their model suggests that order type is serially uncorrelated.

Biais et al. (1995) suggest follow-on order strategies that may account for positive serial correlation in order flow. First, traders may strategically split large orders to reduce price impact. Second, if certain market participants can observe the orders of others whom they believe to be informed, then they may imitate their orders. Third, news events may lead various traders to trade in a similar manner. Yeo (2002) offers another follow-on order strategy based competition between limit order submitters. Suppose there is an existing limit sell order at $30.00 and a new limit sell arrives at $29.99 taking precedence by price priority. The initial seller may cancel the $30.00 order and submit a new limit sell at $29.98. Thus, limit sell follows limit sell.

Negative order-by-order serial correlation in order-type hypothesis (Parlour). The probability of observing a given order type is *lowest* if the immediately preceding event is the same type order.[1]

Zero order-by-order serial correlation in order type hypothesis (Kaniel and Liu). The probability of observing a given order type is *identical* regardless of the immediately preceding event.

Positive order-by-order serial correlation in order type hypothesis (Biais et al. and Yeo). The probability of observing a given order type is *highest* if the immediately preceding event is the same type order.

1.2. Long-run serial correlation in order type

If a trading venue exhibits long-run positive order-type serial correlation, then the limit order book drifts to a replenishment corner solution or an exhaustion corner solution. Either limit orders accumulate leading to arbitrarily large fill times or market orders exhaust all liquidity leading to failure to execute for lack of a counterparty. We do not observe infinite depth at the quoted prices nor, under usual market conditions, an empty limit order book. Hence, market orders (which exhaust liquidity and widen the bid–ask spread) must eventually be followed by limit orders (replenishing liquidity). Under any set of assumptions about informed and uninformed trading, a long-run cycle of exhausting and replenishing liquidity is a necessary condition for long-run equilibrium. Only negative long-run serial correlation in order type can maintain the appropriate balance to produce ongoing trading.

However, the time-scale of what constitutes the "long-run" in order dynamics is unclear. This is complicated by the fact that the NYSE is partially opaque during our sample period. Specifically, the NYSE's best bid and offer are transparent, but the remainder of the limit order book is not. Thus, off-floor traders might be able to condition their order choice only on dated information. Furthermore, humans require time to mentally process market conditions and submit orders. Accounting for this, we aggregate each type of order flow over a variety of time intervals ranging from five seconds to five minutes to estimate the long-run serial correlation in the order type.

Negative long-run serial correlation in order type hypothesis. The change in the quantity of a given order type over a particular time interval is negative if the change in the same order type over the preceding time interval is positive, and visa versa.

1.3. Depth

Beber and Caglio (2002) and Ranaldo (2004) analyze the quoted depth's effect on order submission. We extend their analysis by investigating whether both sides of the quote seem to affect order choice or if only one side seems to matter. Specifically, we test whether large ask (bid) depth appears to be viewed as forecasting a short-term price decrease (increase), leading to more sells (buys). Brown and Jennings (1990) and Blume et al. (1994) demonstrate theoretically that technical analysis can be of use if current price is not a sufficient statistic for all private information. Osler (2003), in the foreign exchange market, and Kavajecz and Odders-White (2004), in the stock

[1] All hypotheses are stated as the alternative.

market, show that the value of technical analysis is tied to information about the limit order book. Thus, we posit that investors might act as if quoted depth is informative about future price changes.

Short-term forecasting hypothesis. Large ask (bid) depth increases the probability of both a limit sell (buy) and a market sell (buy).

We also posit that traders respond to an increase in the quoted depth by competing on price via limit orders that undercut the existing bid and ask prices.[2] This tendency to compete is reinforced by a small tick size during our sample period.[3] Specifically, we test if a larger ask (bid) depth makes it more attractive to "jump-the-queue" by submitting a limit sell (buy) order with a limit price better than the quote and conversely less attractive to submit a limit sell (buy) order with a limit price equal to or worse than the quote. Chakravarty and Holden (1995) conclude that informed limit order traders might undercut existing quoted prices. Wald and Horrigan (2005) solve for the optimal limit order price, which can lead to undercutting.

Jump-the-queue hypothesis. Large ask (bid) depth increases the probability of an inside-the-quote limit sell (buy) and decreases the probability of an at-the-quote or behind-the-quote limit sell (buy).

1.4. Time-of-day hypothesis

Bloomfield et al. (2005) use an experimental, electronic limit-order-book market to model traders' behavior. They find that liquidity provision evolves during the trading day. Informed traders demand liquidity early in the trading session by submitting market orders but supply liquidity later by submitting limit orders. We might not expect as sharp of a result as in Bloomfield et al. (2005). Their experiment has a finite life after which uncertainty about the asset's value is resolved. In real world markets, uncertainty is seldom fully resolved and uncertainty decreases can come when the market is closed as well as during the trading day.

However, there is evidence of 24-hour patterns in information arrival and disclosure. For example, Chung et al. (1999) document a U-shaped pattern in trading activity and Barclay and Hendershott (2003) document a U-shaped pattern in price discovery over the trading day with a much larger spike at the beginning of the day. This suggests that there is more informed trading early in the day. Thus, it is possible that information accumulates overnight when trading is more costly. For example, Greene and Watts (1996) find that two-thirds of sample earnings announcements take place after the stock exchanges close. This implies that many informed traders face an end-of-day deadline for exploiting their information.

Anand et al. (2005) find evidence consistent with the Bloomfield et al. experimental results using the NYSE TORQ data from the early 1990s. Specifically, they find that institutional (informed) limit orders are more profitable early in the day than later and that medium-sized

[2] In Parlour (1998), traders cannot submit inside-the-quote limit orders. However, if we extend her model to allow inside-the-quote limit orders, then the same reasoning would prevail. Specifically, if the previous order was a limit sell lengthening the ask queue, then it is relatively more attractive for the current trader to submit an inside-the-quote limit sell (undercutting the current ask), rather than submitting an at-the-quote limit sell (lengthening the queue). Anand et al. (2005) document that the profitability of institutional (informed) traders' aggressively priced limit order exceeds the profitability of individual (uninformed) investors' orders. Hall and Hautsch (2004) examine how information in an open limit order book affects an order's aggressiveness. Goettler et al. (2005) develop a more generalized model of a limit order book.

[3] Recent work (e.g., Bacidore et al., 2003; Chakravarty et al., 2004) demonstrates the impact decimal prices have had on the NYSE.

institutional marketable orders (their proxy for informed market orders) account for more of the cumulative price movement in the morning than in the afternoon. The latter result suggests that informed investors are most aggressive in their use of market orders early in the day. In a multivariate setting, we determine whether we can identify a change in the likelihood of detecting market/limit orders from the representative investor as the trading day evolves.

In contrast to Bloomfield et al, the economics literature notes a “deadline effect,” where agreements are more likely at the last minute. For example, Roth et al. (1988) conduct experiments testing for bargaining patterns through time and find that many deals occur just before deadlines, suggesting that traders become more aggressive as the close of trading approaches. Harris (1998) and Hollifield et al. (2004) also posit a deadline effect. Beber and Caglio (2002) find evidence consistent with this hypothesis using the NYSE TORQ data and we identify this tendency in low-volume stocks.

Time-of-day hypothesis. As the time of day increases, market orders become less likely and limit orders become more likely.

1.5. Speed versus cost

Boehmer (2005) analyzes market orders on NASDAQ and at the NYSE’s auction market. He finds an inverse correlation between execution speed and trading costs (i.e., the effective spread) and offers a possible explanation for this relationship. In 2000, the NYSE introduced Direct+, an electronic system automatically executing small (fewer than 1100 shares), marketable limit orders against the posted quote. These orders fill immediately and are not eligible for price improvement. If Direct+ customers are willing to forego price improvement, then it is possible that they are less concerned about the size of the quoted spread itself. We analyze marketable orders for fewer than 1100 shares routed to the NYSE’s automatic execution system versus small marketable orders routed to the NYSE’s traditional auction.

Speed versus cost hypothesis. Small marketable orders that are automatically executed are less sensitive to the quoted spread than small marketable orders routed to the auction process.

We simultaneously test these hypotheses while controlling for other variables that extant work finds important. We use a multinomial logit model and electronic order data from the NYSE.

2. Data

We obtain system order data from the NYSE. Because of the enormous volume of data, we select a sample of NYSE-listed equity securities. Initially, we choose the 50 most actively traded NYSE stocks during the 20 trading days prior to January 29, 2001. We also randomly select 25 stocks from each of four volume–price groups. To pick the 100-stock random sample, we rank NYSE-listed securities on share trading volume and, separately, on average NYSE trade price during the 20 trading days prior to January 29, 2001. Each security is placed into one of four categories after comparing its share price to median NYSE share price and its trading volume to median NYSE volume. These groups (of unequal numbers of stocks) are a high-volume:high-price group, a high-volume:low-price group, a low-volume:high-price group, and a low-volume:low-price group. Within each group, we arrange securities alphabetically (by symbol) and choose every Nth security, where N is chosen to select 25 securities from that group. Because 2 of the 50 stocks with the highest trading volume also are randomly chosen as part of the high volume groups, our final sample has 148 securities.

Our dataset is the NYSE's System Order Database (SOD) and its companion quote file (SODQ), which provide an audit trail of system orders arriving during the week of April 30 to May 4, 2001. SOD contains order and execution information for NYSE system orders. Order data include security, order type, a buy–sell indicator, order size, order date and time, limit price (if applicable), and the identity of the member firm submitting the order. Execution data include the trade's date and time, the execution price, the number of shares executing, and (if relevant) cancellation information. SODQ contains the NYSE quote and the best non-NYSE quote at the time an order arrives and at trade time. All records (orders, executions, and cancellations) are time-stamped to the second. System orders represent about 93% of reported NYSE orders and 47% of reported NYSE share volume.[4] These data do not include most of the orders routed to the specialists' trading posts via floor brokers. Thus, we study only a subset of NYSE order choices, those resulting in electronic submission of orders. Generally, these are the smaller, more easily executed orders. Also, our data restrictions might suggest we are studying more impatient traders than those traders choosing floor brokers to fill orders. Our sample includes over 5.1 million events. We exclude orders arriving when the National Best Bid (NBB) price exceeds the National Best Offer (NBO) price or when the NBB or NBO size is zero.[5]

Table 1 provides some descriptive statistics for these and other variables. Mean order size is 1232 shares. Although this is relatively small, we have large orders, as evidenced by the maximum order size of 900,000 shares. On average, our sample stocks have 2.24 million shares traded per day, which is a 0.106% turnover rate. This undoubtedly exceeds the typical NYSE stock because our sample includes the 50 most actively traded NYSE stocks. The average NYSE bid (offer) depth is 2760 (3701) shares. For the sample stocks (again, oriented to the more actively traded NYSE stocks), the spread averages 0.15% of the stock's $43.80 average "price," i.e., bid–ask spread midpoint. We do, however, have some observations where the spread is a large fraction of the stock's price. The average five-minute own and market returns are positive during the sample period. The own return has more cross-sectional volatility than the market return. The day return variable (measured as the change in the quote midpoint between order arrival time and that day's closing) averages 0.27%.

3. Methodology

3.1. Variables

We analyze the likelihood that a "representative trader" makes various choices — the submission of different order types, order cancellations, or doing nothing. We define the "representative trader" as the weighted average over all trader types. With a certain probability, this includes a trader who can cancel outstanding limit orders. In addition, because the representative trader can choose to do nothing, we design a role for clock time passing with no activity. Specifically, we define a no-activity event as a stock-specific time interval passing without an order submission or cancellation. The no-activity time interval is defined as either: (1) the median time between successive order events for a given stock, or (2) five minutes, whichever is less. There is considerable variation across stocks in their no-activity time intervals. The eight most active stocks have a no-activity time interval of one second. The 50 least active stocks have a median time between events exceeding five minutes and, thus, receive a no-activity time interval of five minutes. Easley et al. (1997) use a similar no-activity event to model and estimate the passage of clock time without activity.

[4] See United States Securities and Exchange Commission (2001a), page 5.

[5] The National Best Bid (Offer) price is the higher (lower) of the NYSE bid (ask) and the best non-NYSE bid (ask).

Table 1
Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Daily share volume	2,242,779	1,555,359	555	6,454,023
Shares outstanding (in 000)	2,118,639	1,942,579	61	9,932,929
National Best Bid size ('00)	27.60	68.57	1	5,880
National Best Offer size ('00)	37.01	103.59	1	8,376
Spread midpoint ($)	43.80	23.04	0.525	118.9
Spread ($)	0.0523	0.0492	0.00	6.14
Percent spread	0.15	0.20	0.00	26.15
Last event market buy	0.1250	0.3306	0	1
Last event market sell	0.1266	0.3320	0	1
Last event limit buy	0.1641	0.3702	0	1
Last event limit sell	0.1546	0.3615	0	1
Own return	0.000141	0.009252	−0.086896	0.106667
Market return	0.000058	0.001043	−0.002974	0.004434
Day return	0.002676	0.015272	−0.121806	0.249431

This table reports descriptive statistics for the sample of 148 stocks trading on the New York Stock Exchange during the week of April 30–May 4, 2001. Order size is the pooled time series cross-sectional average of the number of shares submitted in orders. Daily share volume is the pooled time series cross-sectional average of the volume in shares transacted. The shares outstanding variable is the volume weighted average of the shares outstanding for the firms in the sample. The National Best Bid Size is the size associated with the lowest bid price across all markets quoting the stock. The National Best Offer size is the size associated with the highest ask price across all markets quoting the stock. Percent spread is the national best bid–ask spread divided by the average of the National Best Bid price and the National Best Ask price. Time is the number of five-minute intervals since midnight. Own return is the change in the midpoint of the security's bid–ask spread over the 5 min prior to the order arrival or cancellation. Market return is the change in the midpoint of the bid–ask spread of the exchange traded fund the S&P 500. Index. Day return is measured as [(closing quote midpoint) − (order-time quote midpoint)] / (order-time quote midpoint).

Beginning with each day's first trade, we compute the time between successive pairs of order submissions/cancellations. If the elapsed time exceeds the no-activity interval, then we insert the appropriate number of no-activity events. For example, suppose that a stock has a median time between order activity events of twenty seconds and that orders arrive at 9:30:00, 9:30:05, and 9:30:50. There are fewer than twenty seconds between the first and second order, so a no-activity event is NOT inserted. Between the second and third order, we insert no-activity events at 9:30:25 and 9:30:45. The 16:00:00 closing is taken as the trading day's end. We have four order types: Market Buy, Market Sell, Limit Buy and Limit Sell. We see in Table 1 that these order types account for 57% of the events (=0.1250+0.1266+0.1641+0.1546). Thus, a cancellation/no-activity event occurs 43% of the time.

Our extended analysis differentiates among four limit order types by the aggressiveness of the limit price: behind-the-quote, at-the-quote, inside-the-quote, and marketable. We put each limit order into one of the categories by comparing the limit price to NYSE quoted prices. Behind-the-quote buy (sell) orders have limit prices less (more) than the bid (ask) price. At-the-quote buy (sell) orders have limit prices equal to the bid (ask) price. Inside-the-quote orders have limit prices between the NYSE bid and ask prices. Finally, buy (sell) marketable limit orders have limit prices greater (less) than or equal to the ask (bid) price. Behind-the-quote limit orders are the least aggressive and market orders are the most aggressive. We distinguish between the cancellations of buy and sell orders. To identify the model, one event must be designated as the base case. We arbitrarily designate the no-activity event as our base case.

Based on our hypotheses, we identify nine explanatory variables; defined below.

1. *Last event market buy* takes the value of 1 if the previous event was a market buy order and 0 otherwise;
2. *Last event market sell* takes the value of 1 if the previous event was a market sell order and 0 otherwise;
3. *Last event limit buy* takes the value of 1 if the previous event was a limit buy order and 0 otherwise;
4. *Last event limit sell* takes the value of 1 if the previous event was a limit sell order and 0 otherwise;
5. *Last event cancel buy* takes the value of 1 if previous event was cancellation of a buy order and 0 otherwise;
6. *Last event cancel sell* takes the value of 1 if the previous event was cancellation of a sell order and 0 otherwise;
7. *Relative NYSE bid size* is the size (in hundreds of shares) associated with the NYSE's bid price at the time of the event divided by the number of shares outstanding (in millions);
8. *Relative NYSE ask size* is the size (in hundreds of shares) associated with the NYSE's ask price at the time of the event divided by the number of shares outstanding (in millions);
9. *Time* is the time of day of the event expressed as the number of five-minute intervals since midnight (e.g., 9:30:00 am to 9:34:59 am is interval 114).

We use variables 1 to 6 to test the Order-by-order serial correlation in order type hypotheses, variables 7 and 8 to test the Short-term forecasting hypothesis and Jump-the-queue hypothesis, and variable 9 to test the Time-of-day hypothesis.

Other variables posited to affect order choice are quoted spread (Cohen et al., 1981; Harris, 1998; Foucault, 1999; Wald and Horrigan, 2005), trader patience (Handa and Schwartz, 1996; Foucault et al., 2005), volatility (Foucault, 1999; Wald and Horrigan, 2005), prior own and market return (Brown and Jennings, 1990; Blume et al., 1994), and the expected return on a stock (Wald and Horrigan, 2005).

We control for these and other variables as follows:

1. *Relative volume* is the natural logarithm of the number of shares traded in the five-minute interval prior to the event divided by the number of shares outstanding;
2. *Own return* is the percent change in the stock's midpoint (i.e., the average of the best bid and best ask prices) in the five-minute interval before the event;
3. *Own return squared* is the stock's own return squared (our proxy for stock price volatility);
4. *Market return* is the percentage change in the quoted spread's midpoint for the exchange traded fund mimicking the S&P 500 (SPY) in the five-minute interval prior to the event;
5. *Time from noon squared* is the deviation of the event's time interval from the mid-day time interval (153) squared;
6. *Day return* is calculated as [(closing NYSE quoted spread midpoint) − (order-time NYSE quoted spread midpoint)] / (order-time NYSE quoted spread midpoint);[6] and,

[6] Note that the Day-Return variable controls for the existence of private information; similar to focusing on trading days with a 5% or more return in the sample period used by Anand et al. (2005) or including expected return as in Wald and Horrigan (2005). They wished to examine only stocks with a greater-than-average likelihood of an information effect. We can eliminate this variable without meaningfully affecting our conclusions.

7. *NYSE not at the NBBO* is a binary variable equal to one in the case that the NYSE bid is *not* equal to the National Best Bid or in the case that NYSE offer is *not* equal to the National Best Offer and it is equal to zero otherwise.
8. *Percentage spread* is measured as the NYSE bid–ask spread divided by the average of the bid and ask prices at the time the order is submitted;[7]

3.2. Models

We specify the following multinomial logit model for each stock i and time t over which an event can occur.

$$\begin{aligned}\text{Event type}_{i,t} = {} & a + b_1(\text{Last event cancel buy})_{i,t} + b_2(\text{Last event cancel sell})_{i,t} \\ & + b_3(\text{Last event limit buy})_{i,t} + b_4(\text{Last event limit sell})_{i,t} \\ & + b_5(\text{Last event market buy})_{i,t} + b_6(\text{Last event market sell})_{i,t} \\ & + b_7(\text{Relative NYSE bid size})_{i,t} + b_8(\text{Relative NYSE ask size})_{i,t} \\ & + b_9(\text{Time})_{i,t} + b_{10}(\text{Percentage spread})_{i,t-1} \\ & + b_{11}(\text{Relative volume})_{i,t-1} + b_{12}(\text{Own return})_{i,t-1} \\ & + b_{13}(\text{Own return squared})_{t-1} + b_{14}(\text{Market return})_{t} \\ & + b_{15}(\text{Time from noon squared})_{t} + b_{16}(\text{Day Return})_{i,t} \\ & + b_{17}(\text{NYSE not at NBBO})_{i,t} + e_{i,t} \end{aligned} \tag{1}$$

In Eq. (1), the subscript "t" represents a contemporaneous value and "$t-1$" represents an aggregate value from the preceding five-minute interval. To compute the values for these five-minute intervals, we begin with the 9:30:00-to-9:34:59 interval. We proceed to compute values for each five-minute interval throughout the day, ending with the time from 3:55:00 to 4:00:00. Thus, for example, the "$t-1$" interval associated with an order arriving at 9:42:30 is the 9:35:00–9:39:59 interval. We run two types of multinomial logit models with different event structures.[8]

Initially, we analyze a 7-way event structure. These events are: (1) cancellation of an existing buy order, (2) cancellation of an existing sell order, (3) arrival of a limit buy order, (4) arrival of a limit sell order, (5) arrival of a market buy order, (6) arrival of a market sell order, or (7) no activity in a stock-specific time interval since the last event.[9] We also distinguish between marketable orders routed to the NYSE's Direct+ system and those sent to the traditional auction system. Next, we conduct a more detailed analysis using a 13-way event structure: (1) cancellation of a buy order, (2) cancellation of a sell order, (3) arrival of a behind-the-quote limit buy, (4) arrival of an at-the-quote limit buy, (5) arrival of an inside-the-quote limit buy, (6) arrival of a marketable limit buy, (7) arrival of a behind-the-quote limit sell, (8) arrival of an at-the-quote limit sell, (9) arrival of an inside-the-quote limit sell, (10) arrival of a marketable limit sell, (11) arrival of a market buy, (12) arrival of a market sell, or (13) no activity in a stock-specific time interval since the last event. Examining both event classification schemes is useful because some of our hypotheses focus on a general category of orders, while other

[7] We obtain similar results if we use both dollar spread and inverse price in the regressions.

[8] Our approach can be thought of as randomly selecting a single representative trader and assessing his/her actions. We do not model the number of traders present in the market at a particular time.

[9] For this analysis, the Market Buy (Market Sell) event includes market and marketable limit buy (sell) orders, as both types of orders are liquidity-demanding, executable orders. The Limit Buy (Limit Sell) event includes only non-marketable limit orders, because these orders supply liquidity. For expositional clarity, we use the terminology "market order" and "limit order" terminology.

hypotheses have predictions regarding a specific order type (e.g., the Order-by-order Serial Correlation in Order Type Hypotheses is concerned with limit orders in general while the Jump-the-queue hypothesis focuses on inside-the-quote limit orders). It is possible that each individual type of limit order provides statistically insignificant changes in probability, but taken together the probability change associated with limit orders is statistically significant. Similarly, the 7-way allows us to classify marketable limit orders a market orders together when appropriate and the 13-way allows us to consider them separately when appropriate.

4. Results

4.1. Basic 7-way event structure

To the extent possible, we estimate Eq. (1) separately for each stock. For 85 sample stocks, the maximum likelihood regression converges. The stocks not converging are low-volume stocks with few observations. We aggregate the data from these stocks in one regression, which converges. Thus, for our stock-by-stock analysis, we have 86 observations.[10] Because low-volume stocks are represented as a single observation, our results are weighted towards higher volume stocks. Below, we examine each of the sample volume portfolios separately to determine the sensitivity of our results to cross-sectional differences in volume.

Panel A of Table 2 reports the mean coefficient estimates of the multinomial logit for the basic 7-way event structure estimated on a stock-by-stock basis. It is standard to compute the marginal effects of the logistic function for changes in the explanatory variables. We compute these and report them in Panel B of Table 2. Marginal effects are the changes in the probability of the dependent variable (row) caused by a one standard deviation shock in the explanatory variable (column). Each event's benchmark probability is the estimated logistic function evaluated at the means of the explanatory variables. To compute the change in the probabilities (marginal effects), we re-evaluate the estimated logistic function after adding a standard deviation to the mean of one explanatory variable without disturbing the other explanatory variables' means. Thus, the column labeled "Rel. ask size" in Panel B of Table 2 reports the marginal effect of a one standard deviation increase in the relative ask size holding all other explanatory variables constant at their mean levels.

4.1.1. Order-by-order serial correlation in order type

We examine the order-by-order serial correlations in order types. Consider marketable orders. In Table 2, we see that marketable buy (sell) orders are most likely to follow marketable buy (sell) orders. That is, the largest marginal effect in the "Last mkt. buy" ("Last mkt. sell") column is associated with marketable buy (sell) orders.[11] Similarly, for limit buy (sell) orders, the likelihood of a limit buy (sell) coming next increases the most. This positive diagonal effect is consistent with the Positive order-by-order serial correlation in order type hypothesis based on Biais et al.

[10] We also estimate Eq. (1) for all stocks simultaneously (not reported). It yields similar conclusions. The stock-by-stock analysis, with its 86 observations, is a conservative approach to the statistical test compared to the panel regression's millions of observations. Assuming only 86 observations also is conservative relative to reporting average test statistics from the regressions, which have thousands of observations.

[11] Following our stated approach, the marginal effects in this subsection are based on a one standard deviation shock from the mean of the independent variable. We also investigate what happens when one of the "last" variables in set equals to 1 and the other "last" variables are set equal to 0. We obtain qualitatively similar results.

Table 2
Estimation of the 7-way event structure for individual orders

Event	Last can. buy	Last can. sell	Last limit buy	Last limit sell	Last mkt. buy	Last mkt. sell	Rel. bid Size	Rel. ask size	Time	Percent spread	Rel. vol.	Own Ret.	Own ret. sqr.	Mkt. ret.	Time sqr.	Day ret.	NYSE not at NBBO
Panel A: mean estimated regression coefficients																	
Cancel buy	10.773	1.045	1.560	1.016	1.005	0.876	−1.041	−0.200	0.068	39.28	0.99	45.308	1.36	82.925	.380	2.085	0.28
Cancel sell	0.888	1.712	1.002	1.512	0.735	1.095	−0.108	−0.558	−2.006	36.70	1.15	−25.53	1.54	−70.07	.419	0.406	0.35
Limit buy	1.506	1.101	1.354	0.924	0.951	0.865	0.574	−0.318	1.905	136.46	1.32	2.442	1.47	81.602	.404	7.154	0.34
Limit sell	1.114	1.520	0.960	1.317	0.842	.0997	−0.362	0.399	0.837	154.9	1.41	18.010	1.49	−84.91	.443	−10.53	0.38
Market buy	0.757	0.570	0.674	0.575	1.089	0.469	0.835	−0.018	1.074	−132.8	1.17	90.639	1.67	121.96	.768	9.068	0.28
Market sell	0.504	0.855	0.612	0.732	0.647	1.074	0.207	0.611	−0.043	−114.0	0.77	−104.8	1.14	−105.4	.719	−12.90	0.17
No activity	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: mean marginal effects (%)																	
Cancel buy	**2.41**	**0.812**	**2.21**	**0.83**	**0.80**	**0.45**	**−0.32**	**−0.16**	−0.07	0.04	**0.14**	**0.57**	**0.51**	**0.47**	**0.20**	0.01	**0.26**
Cancel sell	**0.83**	**2.171**	**0.71**	**2.08**	**0.32**	**0.83**	−0.14	**−0.39**	**−0.16**	0.06	**0.14**	**−0.57**	**0.52**	**−0.34**	**0.42**	−0.12	**0.28**
Limit buy	**2.72**	**1.023**	**3.93**	**1.18**	**1.31**	0.80	**0.69**	**−0.41**	**0.48**	**3.17**	**0.38**	**1.08**	**0.64**	**0.28**	**0.63**	**0.71**	**0.49**
Limit sell	**0.99**	**2.559**	**1.02**	**3.40**	**0.73**	**1.18**	**−0.39**	**0.55**	**0.38**	**3.50**	**0.48**	**−1.13**	**1.04**	**−0.38**	**0.79**	**−0.75**	**0.66**
Market buy	0.01	**−0.263**	**0.15**	−0.12	**1.58**	**0.12**	**0.48**	0.01	0.068	**−2.13**	**0.31**	**1.57**	**0.40**	**0.64**	**1.64**	**0.40**	0.02
Market sell	**−0.23**	**0.166**	**−0.09**	**0.26**	**0.21**	**1.87**	0.04	**0.34**	**−0.23**	**−1.98**	0.21	**−1.34**	**0.45**	**−0.35**	**1.53**	**−0.60**	0.13
No activity	**−6.74**	**−6.468**	**−7.95**	**−7.64**	**−4.98**	**−5.27**	−0.36	0.06	−0.45	**−2.67**	**−1.70**	**−0.59**	**−3.60**	−0.10	**−5.20**	0.36	**−1.86**
Panel C: hypothesis predicted signs of the marginal effects																	
Cancel buy																	
Cancel sell																	
Limit buy			**+ vs −**				**+**		**≠0**								
Limit sell				**+ vs −**				**+**	**≠0**								
Market buy					**+ vs −**		**+**		**≠0**								
Market sell						**+ vs −**		**+**	**≠0**								
No activity																	

This table reports the results from estimating Eq. (1) on a stock-by-stock basis. In Panel A, we report the mean of the estimated regression coefficients. In Panel B, we report the mean of the marginal effects (change in the probability of an event caused by a one standard deviation shock in the explanatory variable). In each panel we report the mean from 86 regressions. For 85 of our sample stocks, the maximum likelihood estimation of Eq. (1) converges. For the other sample stocks, we pool data into an eighty-sixth regression. Coefficients for bid size, ask size, time, and time squared are multiplied by 1000. Coefficients for relative volume (own return squared) are multiplied by 1,000,000 (10,000). **Bold numbers** are significant at the .01 level with both a standard cross-sectional t-test and a Chi-square test of proportions using the 86 regressions on the regression coefficient estimates in Panel A and the marginal effects in Panel B. The test of proportions tests the null hypothesis that significantly more than one-half of the individual coefficient estimates (in Panel A) or marginal effects (in Panel B) have the same sign as the mean.

(1995) and Yeo (2002).[12] It is inconsistent with the Zero order-by-order serial correlation in order type hypothesis based on Kaniel and Liu (2005) and with the Negative order-by-order serial correlation in order-type hypothesis based on Parlour (1998).

We also examine the probability changes associated with cancelled orders. Our results are consistent with traders canceling existing limit orders and submitting new ones. If a buy (sell) order is cancelled, then the most likely subsequent event is a new buy (sell) limit order.

Most of the marginal effects associated with the last event variables are positive. This suggests that order activity is clustered — the arrival of or cancellation of any type of order significantly increases the likelihood of additional order activity and decreases the likelihood of no activity. No activity also is clustered. To see this, note that the arrival or cancellation of an order significantly decreases the likelihood of a no-activity interval. By implication, if we observe no activity, then the likelihood of a subsequent no-activity interval increases. Thus, we extend the Biais et al. (1995) diagonal effect to no-activity intervals as well.

4.1.2. Depth

Table 2 shows that quoted depth influences orders on both sides of the market. A large ask (bid) depth increases the probability of a limit sell (buy) and decreases the probability of a limit buy (sell). Table 2 also shows that a large ask (bid) depth increases the probability of market sell (buy) orders, supporting the Short-term forecasting hypothesis. Thus, in the short run, a limit order book imbalance attracts additional limit orders on the book's deep side and additional market orders on the book's thin side, increasing the imbalance. This is consistent with positive serial correlation in order type. The fact that depth on the bid (ask) side of the book increases the likelihood of market buy (sell) orders is consistent with the Short-term forecasting hypothesis. Also consistent with the Short-term forecasting hypothesis is the fact that there appears to be a momentum effect and a market effect (a positive own/market return increases the likelihood of buy orders and decreases the likelihood of sells).

4.1.3. Time

After controlling for the U-shaped intra-day pattern in trading activity, increasing time of day increases the probability of limit orders and decreases the probability of market sells. This supports the experimental finding of Bloomfield et al. (2005). It also is consistent with the findings in Anand et al. (2005) that informed investors use market orders more aggressively early in the trading day. We find this in a multivariate analysis controlling for variables hypothesized and demonstrated to be determinates of order choice. This result is inconsistent with Beber and Caglio (2002) who find that the proportion of market orders increases at day's end in the TORQ data from the early 1990s.

4.1.4. Spread

Wide spreads increase the probability of non-marketable orders and deflate that of marketable orders. This is consistent with prior findings in other markets or other time periods by Biais et al.

[12] As a robustness check on the positive serial correlation in order type, we use two alternative specifications. First, we estimate the 7-way event structure but drop the spread, bid depth, and ask depth explanatory variables. Second, we estimate the 7-way event structure eliminating the spread, bid depth, ask depth, volume, and volatility variables. It is possible that these transparent (to off-floor traders) explanatory variables absorb some impact of the less transparent Last Event variables. In unreported results, the positive serial correlation in order type (positive diagonal effect) is as strong in these alternative specifications.

(1995), Harris (1998), Hollifield et al. (2004), Smith (2000), Bae et al. (2003), Ranaldo (2004) and Wald and Horrigan (2005).

4.1.5. Volume and own return

Table 2's marginal effects suggest momentum; positive (negative) own returns in the prior five minutes are associated with an increased likelihood of buy (sell) orders. Campbell et al. (1993) model a market in which risk-averse market makers accommodate uninformed traders' demands but require compensation in the form of price reversals from price pressure. Because public information is likely to impact price with little trading volume in their model, this leads to a dichotomy; price changes accompanied by high volume are more likely to be reversed than price changes with low volume. To determine whether traders appear to condition their order choice on both volume and price change, we examine the combined marginal effects of price and volume. Specifically, we ask whether the trading strategy appears different under high volume:high return scenarios versus low volume:high return scenarios. We find that volume's marginal effects are uniformly positive, suggesting that the hypothesis of Campbell et al. is not supported by our data.

4.2. Auto-ex orders vs. auction-process orders

Next, we expand the analysis to compare orders routed to the automatic execution system (Direct+) versus orders routed to the floor's auction process. In 2001, Direct+ accepted orders of only 1099 shares or fewer. Therefore, we subdivide marketable orders into auto-ex, small auction, or big auction, where small orders are defined as fewer than 1100 shares and big orders exceed 1099 shares. Thus, we estimate an 11-way event model: (1) cancel buy; (2) cancel sell; (3) limit buy; (4) limit sell; (5) big auction marketable buy; (6) big auction marketable sell; (7) small auction marketable buy; (8) small auction marketable sell; (9) auto-ex marketable buy; (10) auto-ex marketable sell; and, (11) no activity. We pool data across stocks for this regression, so our results are dominated by higher volume stocks. With this approach's large number of observations, all of the marginal effects are statistically significant.

Table 3 shows the marginal effects for the 11-way event model. The marginal effect of the percent spread on auto-ex marketable buys is −0.13, compared with −2.59 on small auction marketable buys. The marginal effect of the percent spread on auto-ex marketable sells is −0.06, versus −2.54 on small auction marketable sells. This order-of-magnitude difference is consistent with the Speed versus cost hypothesis. Direct+ traders, who by definition are willing to forego price improvement to get speed, also pay little attention to the size of the quoted cost of immediacy. Our results complement the finding of a cost–speed trade-off in Boehmer (2005) for the NASDAQ market and the NYSE auction market.

A striking result is that the auto-ex orders' marginal effects are all much smaller than those of the small auction orders for all of the explanatory variables. The small auction orders are often two orders of magnitude more sensitive to market conditions than are Direct+ orders. Regardless of how we measure market conditions, Direct+ orders appear to be relatively insensitive to market conditions and small auction orders have economically meaningful regard for market conditions. This result is also consistent with Handa and Schwartz (1996) who posit that some traders are willing to suffer higher trading costs in order to gain speed of execution.

We hasten to add that this result does not imply irrationality on the part of these traders. It may simply reflect different investment styles. For example, Keim and Madhavan (1997) study a large sample of institutional traders with different investment styles. They find that "value" investors, who exploit relatively long-term information, trade in a relatively patient manner incurring low

Table 3
Separating small automatically executed orders and small auction orders

Event	Last can. buy	Last can. sell	Last limit buy	Last limit sell	Last mkt. buy	Last mkt. sell	Rel. bid size	Rel. ask size	Time	Percent spread	Rel. vol.	Own Ret.	Own ret. sqr.	Mkt. ret.	Time sqr.	Day ret.	NYSE not at NBBO
Cancel buy	2.60	1.03	1.90	0.86	0.73	0.39	0.15	−0.15	−0.20	0.63	0.07	0.48	−0.41	0.55	0.31	0.08	0.25
Cancel sell	1.03	2.36	0.83	1.76	0.40	0.80	0.15	−0.76	−0.26	0.89	0.08	−0.15	0.15	−0.56	0.47	−0.08	0.26
Limit buy	1.92	0.89	3.13	1.19	1.17	0.56	−0.35	−0.08	0.12	3.41	0.31	−0.38	0.25	0.56	0.84	0.29	0.72
Limit sell	0.90	1.82	1.17	2.95	0.58	1.18	−0.42	−0.30	0.18	3.37	0.29	0.95	−0.73	−0.56	1.01	−0.43	0.83
Big auction MB	0.02	−0.03	0.11	0.04	0.51	0.12	−0.03	−0.02	−0.03	−0.63	0.15	0.02	−0.02	0.39	0.63	0.07	0.10
Big auction MS	−0.03	0.06	0.03	0.13	0.13	0.57	−0.61	−0.03	−0.07	−0.58	0.13	−0.05	0.06	−0.33	0.66	−0.13	0.12
Small auction MB	0.14	−0.06	0.40	0.09	1.89	0.30	−0.10	−0.41	0.00	−2.59	0.55	−0.14	0.14	1.13	1.32	0.25	0.34
Small auction MS	−0.09	0.21	0.07	0.48	0.32	2.05	0.26	−0.49	−0.23	−2.54	0.46	−0.07	0.09	−1.04	1.19	−0.37	0.29
Auto-ex MB	0.02	0.001	0.02	−0.001	0.03	−0.0001	0.01	−0.02	−0.01	−0.13	0.01	−0.02	−0.03	0.02	0.01	0.01	−0.001
Auto-ex MS	−0.0008	0.01	0.001	0.01	−0.0008	0.02	−0.01	0.002	0.005	−0.06	0.01	0.002	0.003	−0.01	0.005	0.0002	−0.002
No activity	−6.50	−6.30	−7.66	−7.51	−5.77	−5.98	0.96	2.25	0.50	−1.77	−2.05	−0.62	0.48	−0.15	−6.46	0.32	−2.90

We report marginal effects (change in an event's probability due to a shock in an explanatory variable) from a pooled cross-sectional regression. To do this, we estimate Eq. (1) and evaluate the estimated logistic at the explanatory variables' mean values. We then re-evaluate the estimated logistic after adding a one standard deviation to one explanatory variable. Due to the large sample size, all marginal effects are statistically significant at traditional levels. The 2001 automatic execution system only accepted orders that were 1099 shares or less. Small orders are 1099 shares or less and big orders are greater than 1099 shares.

transaction costs. “Index” investors, who wish to rapidly adjust their portfolio for index additions and deletions, trade in a less patient manner. Finally, “technical” investors, who exploit perceived short-term patterns, trade in the most aggressive manner and incur high transaction costs. Thus, the choice of Direct+ might well be exogenous to market conditions.

4.3. Limit order price aggressiveness

We extend the analysis in a different direction to consider order pricing aggressiveness. Specifically, we separate limit buys and limit sells into four sub-categories each: (1) marketable, (2) inside-the-quote, (3) at-the-quote, and (4) behind-the-quote. Table 4 reports the results of a 13-way event structure estimated on a stock-by-stock basis. Panel A reports the mean coefficient estimates from the multinomial logit regression and Panel B presents the mean marginal effects.

Table 4 confirms that the arrival of a limit order increases the likelihood of another non-marketable limit order on the same side of the market for all levels of pricing aggressiveness. Similarly, the most likely event after observing a market buy (sell) order is another market buy (sell) order. This provides additional confirmation of the positive order-by-order correlation in order type. When a buy (sell) order is cancelled, the most likely subsequent event is the arrival of a new buy (sell) limit order. The increase in likelihood of non-marketable limit orders associated with a cancellation is common across all levels of pricing aggressiveness.

Prior research (e.g., Bae et al., 2003; Beber and Caglio, 2002; Wald and Horrigan, 2005) demonstrates that the likelihood of a market order falls as the spread widens. We extend this literature by finding that wide spreads lower the probability of marketable limit orders, in addition to market orders. However, wide spreads increase the probability of inside- and at-the-quote orders limit orders. That is, marketable limit orders respond to the spread more like market orders than non-marketable limit orders and traders compete more heavily to reach the front of the queue when spreads are wide. Table 4 also shows that large ask (bid) depth increases the probability of an inside-the-quote limit sell (buy) and decreases the probability of both at-the-quote or behind-the-quote limit sells (buys). This fully supports the Jump-the-queue hypothesis.

Finally, Table 4 also shows that the likelihoods of at- and inside-the-quote limit orders rise as the end of trading approaches. This is consistent with the experiment in Bloomfield et al. (2005), which finds that informed traders demand liquidity early in the day but later assume the role of market maker and complements the finding in Anand et al. (2005) that informed traders appear to use market orders less aggressively in the afternoon than in the morning.

4.4. Volume and price level

As we must pool the data for low-volume stocks to obtain coefficient estimates, the results reported thus far are more indicative of the higher volume stocks than the low-volume stocks. We focus on each group separately to address this. Recall that our sample securities are selected to provide cross-sectional dispersion across trading volume and security price. We re-estimate the logit model by volume–price subsamples. Table 5 shows these results. Panel A reports mean marginal effects for the 50 most active stocks. Panel B reports mean marginal effects for high-volume:high-priced stocks. Panel C covers high-volume:low-priced stocks. Finally Panel D represents low-volume stocks.

Although the results generally are strongest for the higher volume subsets, most conclusions are consistent across the volume–price groups. A few exceptions are evident. For low-volume stocks, the likelihood of marketable orders falls as the volume and volatility in the prior five-minute interval increases. This might suggest that market orders in low-volume stocks are subject

Table 4
Estimation of the 13-way event structure for individual orders

Event	Last can. buy	Last can. sell	Last limit buy	Last limit sell	Last mkt. buy	Last mkt. sell	Rel. bid size	Rel. ask size	Time	Percent spread	Rel. vol.	Own Ret.	Own ret. sqr.	Mkt. ret.	Time sqr.	Day ret.	NYSE not at NBBO
Panel A. Regression coefficient estimates																	
Cancel buy	**0.46**	**−4.69**	**2.44**	**−2.84**	**2.03**	**−4.06**	−0.43	**−0.43**	−0.19	**48.51**	**0.96**	**12.13**	**1.40**	**36.44**	**0.40**	−1.77	**0.22**
Cancel Sell	**−4.61**	0.33	**−2.98**	**2.46**	**−4.30**	**2.15**	**−0.48**	**−0.26**	−0.54	**56.49**	**1.08**	5.23	**1.44**	**−35.66**	**0.42**	−3.16	**0.28**
BTQ limit buy	**1.26**	**1.15**	**1.51**	**1.20**	**0.82**	**0.84**	**−1.55**	**0.60**	0.08	7.21	**0.86**	−3.68	**0.93**	1.15	**0.74**	8.12	0.08
ATQ limit buy	**1.16**	**1.07**	**1.23**	**0.91**	**0.80**	**0.73**	**−0.87**	−0.09	3.65	**159.0**	**1.31**	54.84	−1.81	**104.9**	**0.27**	4.66	**0.20**
ITQ limit buy	**1.28**	**0.87**	**1.35**	**0.92**	**0.79**	**0.87**	**2.37**	**−2.05**	2.67	**237.2**	**1.28**	6.21	**0.90**	**115.8**	**0.30**	9.34	**0.24**
ITQ limit sell	**1.03**	**1.08**	**0.93**	**1.33**	**0.83**	**1.04**	**−1.85**	**1.64**	0.48	**275.8**	**0.98**	**16.65**	**0.90**	**−126.8**	**0.28**	**−11.16**	**0.31**
ATQ limit sell	**0.71**	**1.32**	**0.74**	**1.40**	**0.71**	**1.06**	0.17	**−0.37**	1.18	**179.7**	**1.19**	**38.43**	**1.30**	**−93.21**	**0.32**	**−14.01**	**0.27**
BTQ limit sell	**1.30**	**1.04**	**0.93**	**1.36**	**0.67**	**0.98**	0.17	**−1.02**	4.04	14.70	**0.96**	−6.38	**1.44**	−4.20	**0.84**	**−7.69**	**0.29**
Mkt. Limit buy	**1.03**	**0.77**	**0.94**	**0.80**	**0.94**	0.44	**1.89**	**−1.00**	−0.09	**−468.3**	**1.34**	34.03	**1.84**	**174.7**	**0.69**	9.28	**0.20**
Mkt. Limit sell	0.51	**1.06**	0.44	**0.78**	0.84	1.38	**−0.74**	**1.27**	**−3.00**	**−379.5**	**1.20**	−15.45	**1.66**	**−131.1**	**−0.68**	**−16.58**	−0.41
Market buy	**0.78**	**0.57**	**0.92**	**0.81**	**1.36**	**0.64**	−0.35	0.29	2.78	2.69	**1.01**	**65.28**	**1.16**	**123.8**	**−0.79**	5.10	−0.15
Market sell	**0.59**	**0.81**	**0.81**	**.093**	**0.61**	**1.40**	−0.46	0.32	1.47	−9.69	−.49	**−76.94**	0.67	**−146.3**	**0.72**	−4.57	0.07
Panel B. Mean marginal effects (%)																	
Cancel buy	0.04	**−1.05**	**1.74**	**−1.15**	**1.06**	**−1.10**	**−0.04**	**−0.07**	−0.04	0.08	**0.03**	0.01	**0.14**	**0.06**	**0.08**	0.01	**0.08**
Cancel Sell	**−0.93**	0.05	**−1.09**	**1.61**	**−1.02**	**1.05**	**−0.04**	**−0.05**	**−0.04**	0.02	**0.04**	0.01	**0.14**	**−0.06**	**0.10**	−0.04	**0.93**
BTQ limit buy	**1.17**	**1.07**	**1.45**	**0.92**	**0.51**	**0.50**	**−0.37**	**0.29**	−0.14	**−0.36**	**0.12**	**−0.15**	**0.34**	−0.00	**0.85**	0.06	**0.18**
ATQ limit buy	**1.09**	**0.02**	**1.80**	**0.44**	**0.65**	**0.41**	**−0.34**	−0.14	**0.42**	**1.07**	**0.10**	−0.12	**0.23**	**0.54**	−0.06	0.27	**0.14**
ITQ limit buy	**1.21**	**0.78**	**1.74**	**0.62**	**0.73**	**0.50**	**1.04**	**−1.07**	**0.32**	**2.26**	**0.22**	0.10	0.17	**0.80**	0.37	**0.57**	**0.29**
ITQ limit sell	**0.70**	**1.15**	**0.54**	**1.56**	**0.44**	**0.74**	**−0.78**	**0.96**	0.19	**2.55**	**0.20**	**0.14**	0.12	**−0.80**	−0.08	**−0.37**	**0.43**
ATQ limit sell	**0.55**	**0.98**	**0.40**	**1.53**	**0.44**	**0.55**	−0.07	−0.23	0.25	**1.17**	**0.16**	**0.28**	**0.31**	**−0.45**	0.01	**−0.43**	**0.22**
BTQ limit sell	**1.00**	**1.03**	**0.86**	**1.20**	**0.86**	**0.45**	**0.14**	**−0.37**	−0.02	−0.10	**0.25**	0.07	**0.35**	0.00	**1.01**	−0.12	0.08
Mkt. Limit buy	**0.32**	**0.12**	**0.28**	**1.69**	**0.69**	**0.18**	**0.27**	**−0.12**	**−0.11**	**−1.64**	**0.16**	0.16	**0.36**	**0.60**	**0.57**	**0.24**	0.05
Mkt. Limit sell	**0.22**	**0.39**	**0.19**	**0.34**	**0.23**	**0.78**	−0.02	**0.23**	**−0.28**	**−1.50**	**0.19**	0.01	**0.39**	**−0.42**	**0.56**	**−0.31**	−0.10
Market buy	**0.59**	**0.23**	**0.60**	**0.39**	**1.60**	**0.46**	**0.20**	**0.11**	**0.18**	**−0.54**	**0.19**	**0.57**	**0.25**	**0.90**	**1.26**	**0.17**	−0.02
Market sell	**0.25**	**0.67**	**0.42**	**0.69**	**0.50**	**1.90**	**0.09**	**0.19**	0.03	**−0.65**	**0.07**	**−0.37**	**0.35**	**−0.99**	**1.12**	**−0.29**	**0.14**
No activity	**−6.24**	**−6.08**	**−8.97**	**−8.97**	**−6.20**	**−6.47**	−0.06	0.28	**0.74**	**−2.36**	**−1.70**	**−0.72**	**−3.20**	**−0.17**	**−5.48**	0.22	**−1.60**

This table reports the results from estimating Eq. (1) on a stock-by-stock basis. In Panel A, we report the mean of the estimated regression coefficients. In Panel B, we report the mean of the marginal effects (change in the probability of an event caused by a one standard deviation shock in the explanatory variable). In each panel we report the mean from 86 regressions. For 85 of our sample stocks, the maximum likelihood estimation of Eq. (1) converges. For the other sample stocks, we pool data into an eighty-sixth regression. BTQ = behind-the-quote; ATQ = at-the-quote; ITQ = inside-the-quote. Coefficients for bid size, ask size, time, and time squared are multiplied by 1000. Coefficients for relative volume and own return squared are multiplied by 1,000,000 and 10,000 respectively. **Bold numbers** are significant at the .01 level using a both a standard cross-sectional *t*-test and a Chi-square test of proportions using the 86 regressions on the regression coefficient estimates in Panel A and the marginal effects in Panel B. The test of proportions tests the null hypothesis that significantly more than one-half of the individual coefficient estimates (in Panel A) or marginal effects (in Panel B) are in the same direction as the mean.

Table 5
Estimation of the 7-way event structure by volume and price category

Event	Last can. buy	Last can. sell	Last limit buy	Last limit sell	Last mkt. buy	Last mkt. sell	Rel. bid size	Rel. ask size	Time	Percent spread	Rel. vol.	Own Ret.	Own ret. sqr.	Mkt. ret.	Time sqr.	Day ret.	NYSE not at NBBO
Panel A: highest volume stocks																	
Cancel buy	2.45	0.95	1.76	0.81	0.69	0.37	−0.28	−0.08	−0.19	0.16	0.16	0.45	0.27	0.24	0.27	0.10	0.26
Cancel sell	0.94	2.25	0.79	1.62	0.39	0.75	−0.17	−0.24	−0.16	0.26	0.13	−0.49	0.37	−0.18	0.38	−0.12	0.26
Limit buy	1.74	0.73	2.66	0.92	0.93	0.42	0.28	−0.15	0.22	3.53	0.41	0.83	0.29	−0.62	0.66	0.51	0.48
Limit sell	0.68	1.56	0.85	2.40	0.42	0.93	−0.23	0.21	0.39	3.61	0.46	−0.74	0.42	0.72	0.62	−0.58	0.44
Mkt. Buy	0.07	−0.17	0.37	0.006	2.10	0.12	0.47	−0.006	−0.02	−2.24	0.41	1.82	0.55	0.06	1.91	0.36	0.02
Mkt. Sell	−0.20	0.15	−0.006	0.45	0.17	2.45	0.03	0.44	−0.30	−2.17	0.27	−1.67	0.54	−0.03	1.79	−0.65	0.09
No activity	−5.69	−5.48	−6.45	−6.24	−4.76	−5.06	−0.25	−0.13	−0.06	−3.15	−1.86	−0.18	−2.46	−0.19	−5.56	0.39	−1.56
Panel B: high-volume, high-price stocks																	
Cancel buy	2.71	0.63	2.74	0.92	0.95	0.53	−0.34	−0.21	0.06	0.02	0.15	0.77	0.49	0.70	0.07	−0.07	0.25
Cancel sell	0.71	2.36	0.65	2.47	0.21	0.88	−0.20	−0.38	−0.10	−0.07	0.09	−0.63	0.41	−0.68	0.49	−0.01	0.47
Limit buy	3.12	1.39	6.07	1.32	1.76	1.13	1.12	−0.64	1.12	2.28	0.25	1.21	0.72	−0.14	0.87	1.06	0.79
Limit sell	1.36	2.98	1.02	4.72	1.07	1.36	−0.43	0.96	0.62	2.93	0.40	−1.53	1.00	0.09	1.02	−0.77	1.20
Mkt. Buy	0.05	−0.29	−0.08	−0.21	0.94	0.17	0.58	0.01	0.10	−1.82	0.17	0.87	0.39	1.12	1.17	0.44	0.06
Mkt. Sell	−0.24	0.16	−0.22	0.07	0.20	0.99	0.06	0.43	−0.23	−1.69	0.12	0.84	0.38	−0.51	1.20	−0.46	0.11
No activity	−7.72	−7.24	−10.90	−9.31	−5.15	−5.08	−0.78	−0.17	−1.58	−1.64	−1.20	−0.58	−3.41	0.41	−4.84	−0.18	−2.91
Panel C: high-volume, low-price stocks																	
Cancel buy	1.80	0.63	2.69	0.73	0.87	0.59	−0.46	−0.24	0.13	−0.24	0.06	0.70	0.64	0.79	0.14	−0.20	0.21
Cancel sell	0.73	1.60	0.56	2.80	0.28	0.93	−0.43	−0.33	−0.22	−0.33	0.26	−0.68	0.87	−0.35	0.41	−0.28	0.07
Limit buy	4.85	1.27	4.41	1.71	1.60	1.32	1.35	3.52	0.36	3.52	0.51	1.78	1.14	0.39	0.25	0.73	0.22
Limit sell	1.35	4.69	1.49	4.23	1.00	1.52	−0.83	4.13	0.03	4.13	0.69	−1.71	0.77	−0.07	0.96	−1.16	0.48
Mkt. Buy	−0.27	−0.44	−0.11	−0.33	0.97	0.04	0.43	−2.22	0.27	−2.22	0.22	0.85	0.42	1.73	1.47	0.37	0.003
Mkt. Sell	−0.31	.017	−0.17	−0.02	0.24	1.34	0.06	−1.83	−0.07	−1.83	0.17	−0.77	0.79	−1.09	1.22	−0.60	0.26
No activity	−8.15	−7.09	−8.87	−9.13	−4.99	−5.78	−0.12	3.00	−0.50	−3.00	−1.94	−1.40	−4.65	−0.17	−4.48	1.15	−1.06
Panel D: low-volume stocks																	
Cancel buy	3.59	.98	4.11	.86	1.50	.43	.05	.003	−.60	−.39	.004	.043	9.73	.71	.25	.68	1.21
Cancel sell	.57	2.86	.87	3.76	.27	1.65	−.08	−.07	−.65	.13	.03	−1.54	3.90	−.31	.46	−.18	.67
Limit buy	6.07	2.34	8.79	1.55	3.73	2.70	−.08	−.22	.004	.17	.07	−1.23	7.95	1.58	.39	2.33	1.42
Limit sell	1.81	5.91	1.62	7.56	3.07	3.48	−1.06	.15	−.25	.56	.07	−1.28	34.84	−1.75	1.02	−1.49	1.99
Mkt. Buy	.01	−.57	−.49	−.62	1.32	.33	.16	−.06	.42	−1.75	−.001	16.46	−6.78	.21	1.36	1.56	0.52
Mkt. Sell	−.17	.28	.11	.22	1.28	2.56	.16	.01	.31	−1.50	−.01	−5.51	−7.23	−.06	1.21	−1.14	0.14
No activity	−11.90	−11.83	−45.40	−13.35	−11.19	−11.17	.85	.19	.77	2.77	−.17	−6.92	−42.42	−.38	−4.71	−1.75	−5.51

This table reports the mean marginal effects (change in the probability of an event caused by a one standard deviation shock in the explanatory variable) derived from Eq. (1) estimates.

to sloppy executions in difficult markets and/or that traders in these stocks use limit orders to protect themselves from adverse selection. For low-volume stocks, there is evidence consistent with the claim that traders switch from limit to market orders as the day passes.

4.5. Robustness

We examine order choice conditional on order size, trading volume, and price level and adjust for split orders and end of day effects, but do not report results to conserve space. Wide spreads greatly increase (decrease) the likelihood of small limit (market) orders, moderately increase (decrease) that of medium limit (market) orders, but have little effect on large orders. This is likely because a large order's size dwarfs the quoted depth, making the quoted spread a less relevant predictor of trading cost for these orders. In general, we note that most of the marginal effects are smaller for large orders. This is likely because traders submit large orders only when their impact will be least.

Traders can divide an order into several, smaller orders if that is optimal. Using the raw data, we might misestimate the coefficients by treating each order as a separate trading decision when one decision might result in several orders. This is particularly true of the marginal effects associated with the last event variables. Our data identify the member firm submitting the order and the branch office from which the order is submitted. We assume that an order originating in the same branch of the same broker on the same side of the market as the prior order is a split order. We keep the first order in a series of consecutive "identical" orders and delete the successive orders as the outcome of order splitting. We re-estimate the logit model after eliminating "identical" orders. Except for minor differences in some marginal effects associated with quoted size and own return, there are no major departures from the results discussed above. In particular, the positive serial correlation in order type for individual orders is maintained.[13] Thus, similar to Griffiths et al. (1998) and Yeo (2002), order splitting is not the (complete) explanation for positive autocorrelation in order flow. Thus, it seems that the positive serial correlation in order flow is not due to a purely mechanical effect of traders splitting their large orders into a quick sequence of smaller orders. This suggests that traders might mimic other traders' strategies or might respond similarly to particular events.

Cushing and Madhavan (2000) find that immediacy is in high demand at the close of trading. Although our time and time-from-noon-squared variables address time-of-day effects, we re-estimate Eq. (1) using only orders submitted after 15:14:59. The marginal effects associated with quoted size indicate that traders are less willing to join a queue toward the end of trading. When bid (ask) size is large, traders are less likely to submit buy (sell) limit orders. There also is less evidence of momentum trading at day's end. Finally, the time and time squared variables suggest less trading at the end of our interval than at the beginning.[14]

4.6. Order flow aggregated over clock-time intervals

We are particularly interested in whether order-type correlation remains constant over longer periods of time. Hence, we analyze order choice aggregated over clock-time intervals. As a starting point, consider a simple plot of aggregate buys and aggregate sells over five-minute intervals for a

[13] Note that we do not attempt to control for all possible order splitting strategies. We simply try to determine if order splitting strategies explain the positive serial correlation in order type. We also note that not all of the orders in these stocks are routed to the NYSE. Regional exchanges, NASD market makers and Electronic Communication Networks receive orders in these stocks. This suggests that we might not fully characterize order splitting strategies.

[14] Eliminating time and time-from-noon-squared does not change our conclusions on the other variables.

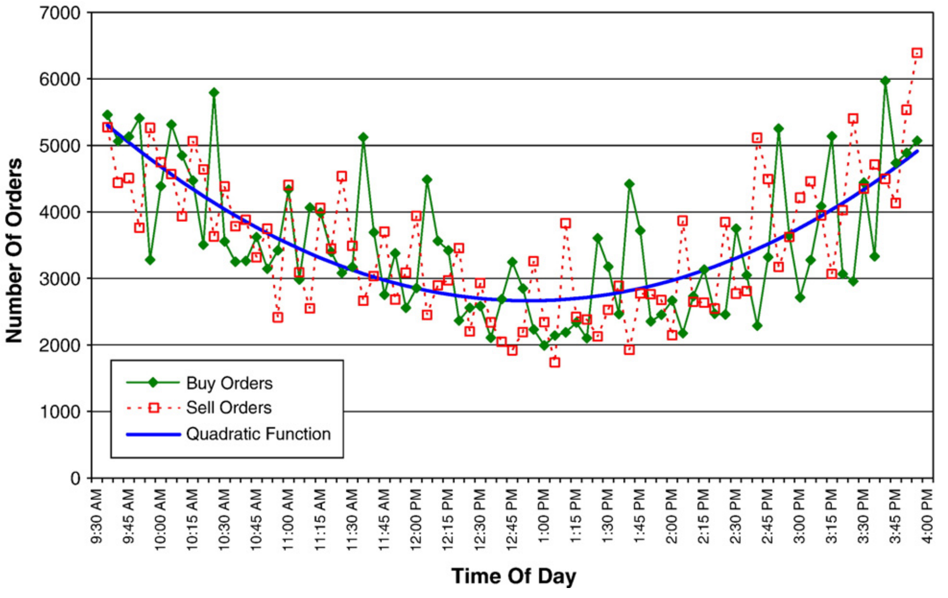

Fig. 1. Aggregate buy and sell orders by time of day.

single day in our sample period. Fig. 1 shows the total number of buy orders (solid diamonds) and sell orders (empty squares) submitted in five-minute intervals for the sample stocks by time of day for 1 day. A quadratic function (the solid curve) is fitted to the data by choosing the quadratic parameters to minimize the sum of squared errors.

We find a U-shaped pattern in order arrival over the trading day similar to what others have found for volume. In addition, there seem to be alternating buy "waves" and sell "waves." Indeed, the deviations of the buy orders from the quadratic function and the deviations of the sell orders from the quadratic function have a negative correlation of −33.6% for this particular day.[15]

We aggregate the dependent variables over various clock-time intervals. Specifically, we define an order flow process for the seven event types (market buy, market sell, limit buy, limit sell, cancel buy, cancel sell, no activity) by aggregating the number of events during a given number of seconds in the trading day. Autocorrelations for these seven-order flow processes suggest that the order flow processes are (statistically) non-stationary.

Standard ARIMA methodology suggests that we first difference the apparently non-stationary order flow processes. So, we redefine each process as the change in the number of events (market buy, market sell, limit buy, limit sell, cancel buy, cancel sell, no activity) over various time intervals. Similarly, the new versions of the "last event" variables are "lag change" explanatory variables, defined as the change in the number of each type of event for a given stock from the previous lag–two time interval compared to the lag–three time interval.[16] In the same spirit, the new version of

[15] Although each day in the sample period has waves of buying and selling, the timing of these waves throughout the day varies from day to day. Thus, aggregating buying and selling over multiple days would produce nearly random variation around the u-shaped intra-day pattern.

[16] The lag change needs to be defined as the lag 2 level minus the lag 3 level in order to avoid a spurious serial correlation. It is easy to show that the correlation of (current level − lag 1 level) with (lag 1 level − lag 2 level) is equal to −1/2, because of the overlapping lag 1 level.

spread, bid size, and ask size are the average spread and average bid and ask sizes over a given time interval. NYSE at the NBBO becomes the fraction of a given time interval that the NYSE quoted prices match *both* the best bid and the best offer.

Thus, revised Eq. (1) for stock i aggregated over a time interval t becomes:

$$\begin{aligned}(\Delta \text{ number events of type} j)_{i,t} = {} & a + b_1(\text{lag } \Delta \text{ number cancel buys})_{i,t} \\ & + b_2(\text{lag } \Delta \text{ number cancel sells})_{i,t} \\ & + b_3(\text{lag } \Delta \text{ number limit buys})_{i,t} \\ & + b_4(\text{lag } \Delta \text{ number limit sells})_{i,t} \\ & + b_5(\text{lag } \Delta \text{ number market buys})_{i,t} \\ & + b_6(\text{lag } \Delta \text{ number market sells})_{i,t} \\ & + b_7(\text{Average relative NYSE bid size})_{i,t-1} \\ & + b_8(\text{Average relative NYSE ask size})_{i,t-1} \\ & + b_9(\text{Time})_{i,t-1} \\ & + b_{10}(\text{Average percentage spread})_{i,t-1} \\ & + b_{11}(\text{Relative volume})_{i,t-1} + b_{12}(\text{Own return})_{i,t-1} \\ & + b_{13}(\text{Own return squared})_{t-1} \\ & + b_{14}(\text{Market return})_t \\ & + b_{15}(\text{Time from noon squared})_t \\ & + b_{16}(\text{Day return})_{i,t} \\ & + b_{17}(\text{Percent of time NYSE not at NBBO})_{i,t-1} \\ & + e_{i,t} \end{aligned} \tag{2}$$

where event type j can take one of seven values (market buy, market sell, limit buy, limit sell, cancel buy, cancel sell, and no activity).

We estimate Eq. (2) with different clock-time aggregation periods using Ordinary Least Squares separately for each event type and pooling all of our data.[17] Table 6 reports the estimated regression coefficients. Panels A, B, and C report the results for 10-second, 30-second, and 300-second time aggregations, respectively. Aggregation causes the sample size to become 872,520, 355,119, and 53,996 for ten seconds, thirty seconds, and three hundred seconds, respectively.

We find that changes in the aggregated order flow processes have very different properties than the order-by-order processes. Most of the lag change coefficients are statistically significant. In Panels A, B, and C, examining the shaded diagonal of the lag change coefficients, we see that all of the estimated correlation coefficients are negative (e.g., lag change limit buy has a −0.009 coefficient with limit buy) and nearly all are statistically significant. All of the off-diagonal coefficients in the corresponding four-by-four boxes are positive or less negative than the diagonal coefficients.

In Panel D, we see the diagonal lag change coefficients for time intervals of 5, 10, 20, 30, 60, and 300 s. The average row reports the mean diagonal coefficient for each time aggregation. The average diagonal coefficient row for five seconds is −0.001, which is quite close to zero. Looking across the

[17] It is possible to estimate Eq. (2) using event-time as opposed to clock-time. In this case, a given change is either −1 (where a given type of order arrived at event time $T-1$, but not at event time T), 0 (where a given type of order arrived both at event times $T-1$ and T; or a given type of order arrived neither at event time $T-1$ nor T), or +1 (where a type of order arrives at event time T, but not at event time $T-1$). Using Ordinary Least Squares to estimate Eq. (2) and pooling our data, we find (in results not reported) that serial correlation in events is reliably positive. Thus, order-by-order analysis finds positive serial correlation in order type using either levels of order flow or changes in levels. This result sets the stage for us to determine if there appears to be liquidity exhaustion–replenishment cycles over longer periods.

Table 6
Changes in the number of events by time aggregation

Event	Lag chg cancel buy	Lag chg cancel sell	Lag chg limit buy	Lag chg limit sell	Lag chg mkt. Buy	Lag chg mkt. Sell	Rel. bid size	Rel. ask size	Time	Percent spread	Rel. vol.	Own Ret.	Own ret. sqr.	Mkt. ret.	Time sqr.	Day ret.	NYSE not at NBBO
Panel A: 10-second aggregation																	
Cancel buy	−0.001	−0.002	**−0.012**	**−0.005**	**0.008**	**−0.002**	0.004	−0.014	0.0001	0.277	−0.001	−0.228	0.146	−1.146	−0.001	0.030	**−0.034**
Cancel sell	**−0.003**	**−0.005**	**−0.007**	**−0.011**	**−0.003**	**0.008**	0.003	−0.019	**0.0001**	0.146	−0.001	0.345	−0.226	0.711	−0.001	−0.055	**−0.035**
Limit buy	**−0.034**	−0.002	**−0.009**	**−0.008**	**0.005**	**0.004**	−0.006	−0.105	**0.0003**	**1.664**	−0.003	−0.283	0.220	−2.729	−0.004	0.158	**−0.085**
Limit sell	**−0.008**	**−0.033**	**−0.004**	**−0.008**	**0.004**	**0.004**	−0.007	−0.015	**0.0003**	**1.976**	−0.004	0.207	−0.230	1.557	−0.004	−0.158	**−0.084**
Market buy	**−0.008**	0.000	**0.003**	**−0.003**	**−0.032**	**−0.005**	0.005	0.074	**−0.0001**	**−1.415**	−0.001	−0.224	0.106	**−2.667**	0.002	**0.240**	**0.038**
Market sell	0.001	**−0.006**	0.000	**−0.005**	−0.001	**−0.022**	0.000	0.097	−0.0001	**−0.997**	−0.002	0.311	−0.188	**4.957**	0.002	**−0.265**	**0.035**
No activity	**0.011**	**0.022**	**0.016**	**0.019**	**0.025**	**0.022**	0.002	−0.007	**−0.0002**	−0.171	0.003	−0.077	0.069	−0.406	0.000	0.016	**0.016**
Panel B: 30-second aggregation																	
Cancel buy	**−0.006**	0.000	**−0.023**	**−0.007**	**0.005**	**−0.013**	0.005	−0.015	0.0002	**0.845**	−0.003	**−1.730**	0.708	**−7.343**	−0.002	0.271	**−0.096**
Cancel sell	**0.004**	**−0.015**	**−0.008**	**−0.024**	**−0.007**	**−0.003**	0.004	−0.105	0.0002	**1.270**	−0.003	**2.059**	−1.628	**6.363**	−0.002	**−0.410**	**−0.104**
Limit buy	**−0.053**	−0.002	**−0.013**	**−0.010**	**−0.011**	**0.012**	−0.007	−0.153	**0.0008**	**4.143**	−0.007	**−2.598**	1.996	**−14.093**	−0.011	**0.637**	**−0.278**
Limit sell	0.002	**−0.045**	**−0.005**	**−0.027**	**0.013**	**−0.020**	−0.007	−0.233	**0.0008**	**5.417**	−0.009	1.487	−1.718	**15.633**	−0.010	**−0.924**	**−0.283**
Market buy	**−0.015**	**0.008**	**−0.005**	**0.004**	**−0.057**	**0.026**	0.005	0.299	−0.0003	**−3.370**	−0.003	**−2.761**	1.980	**−18.118**	0.007	**1.435**	**0.105**
Market sell	**0.007**	**−0.017**	**0.010**	−0.001	**0.019**	**−0.089**	0.001	0.107	**−0.0003**	**−1.984**	−0.003	**3.013**	−1.879	**38.815**	0.007	**−1.438**	**0.098**
No activity	**0.023**	**0.016**	**0.012**	**0.017**	**0.009**	**0.026**	0.001	0.006	**−0.0013**	−0.897	0.006	−0.102	0.122	−6.252	−0.001	0.174	**0.102**
Panel C: 300-second aggregation																	
Cancel buy	0.001	**−0.031**	**−0.049**	0.008	**−0.037**	**0.030**	0.002	0.206	**−0.0075**	2.726	−0.015	−6.022	−9.984	**500.727**	0.090	**5.547**	**−0.298**
Cancel sell	**−0.030**	**0.031**	0.007	**−0.055**	**0.008**	**−0.013**	0.030	−0.167	**−0.0061**	3.090	−0.010	**23.607**	−9.161	**−391.115**	**0.132**	**−3.670**	**−0.539**
Limit buy	**−0.023**	**−0.034**	**−0.033**	0.006	−0.008	**0.018**	−0.003	0.487	**−0.0072**	5.731	−0.028	**−128.739**	**120.636**	**287.138**	0.068	**10.651**	**−0.727**
Limit sell	**−0.034**	0.014	−0.008	**−0.057**	**−0.019**	−0.003	0.048	−0.452	**−0.0039**	**7.388**	−0.023	**161.260**	**−131.855**	55.071	0.062	**−6.599**	**−1.271**
Market buy	**0.040**	**−0.062**	**−0.060**	−0.008	−0.004	**0.050**	−0.029	0.867	**−0.0049**	−1.215	−0.040	**−104.950**	**64.529**	**789.896**	0.060	**14.950**	0.296
Market sell	**−0.058**	**0.074**	**0.038**	**−0.016**	**0.023**	**−0.027**	0.038	−0.484	**−0.0075**	−0.716	−0.031	**61.982**	**−39.652**	**−170.209**	0.163	**−12.442**	0.009
No activity	**−0.032**	**−0.051**	**0.037**	**0.031**	**0.031**	−0.004	−0.002	0.124	**−0.0641**	−3.377	0.031	−5.745	18.343	**−437.014**	−0.171	**8.397**	**1.361**

Panel D: diagonal coefficients by time aggregation

	Five seconds	Ten seconds	Twenty seconds	Thirty seconds	Sixty seconds	Three hundred seconds
Limit buy	0.001	**−0.009**	**−0.015**	**−0.013**	**−0.041**	**−0.033**
Limit sell	−0.001	**−0.008**	**−0.017**	**−0.027**	**−0.056**	**−0.057**
Market buy	**−0.004**	**−0.032**	**−0.035**	**−0.057**	**−0.071**	−0.004
Market sell	**−0.005**	**−0.022**	**−0.047**	**−0.089**	**−0.099**	**−0.027**
Average	−0.002	−0.018	−0.029	−0.046	−0.067	−0.030

This table reports the results from estimating Eq. (2). We report the mean of the estimated OLS regression coefficients, where each row is one OLS regression. In each row, the dependent variable is the change in number of order or no activity events for a given stock over the current time interval vs. the previous time interval.

row, the average diagonal coefficient becomes more negative as the time interval increases through the 60-second aggregation interval. We see that the average diagonal coefficient value starts near zero, becomes more negative through the 60-second interval, and remains negative through three-hundred seconds. This strongly supports the Negative long-run serial correlation in order type hypothesis and, thus, supports a cycle of exhausting and replenishing liquidity in long-run equilibrium. The fact that the average diagonal coefficient is less negative at the 300-second aggregation interval than at the 60-second interval might suggest that the typical liquidity cycle is shorter than five minutes.

We might anticipate that the liquidity exhaustion–replenishment cycle varies with trading volume. Firstly, we know that the no-activity interval (the median time between events) is 1 s for many of the highest volume stocks, but is set to five minutes for most of the low-volume stocks. Thus, for the low-volume stocks in our sample, even the 300-second aggregation interval frequently includes only a single event. Secondly, we focus on the demand for and supply of liquidity by public orders. The NYSE specialist is a far more important source of liquidity for low-volume stocks than for high-volume stocks. Madhavan and Sofianos (1998) find that the highest-decile-volume stocks have a specialist participation rate of 16.5%, while the lowest-decile-volume stocks rate is nearly 53%. Thus, to the extent that the specialist supplies liquidity, this crowds out public orders supplying liquidity. These differences are indeed reflected in our conclusions. Fig. 2 graphs the average diagonal coefficient from estimating Eq. (2) by aggregation period for three volume groups.

For the highest volume stocks, the average diagonal coefficient becomes reliably negative within a very short aggregation interval. This takes a bit longer for the high-volume stocks. Both the highest and high-volume stocks display the most negative average diagonal coefficient at the 60-second interval. The average diagonal coefficient for low-volume stocks seems to stay quite close to zero for all aggregation intervals. Examining low-volume stocks at a 1800-second

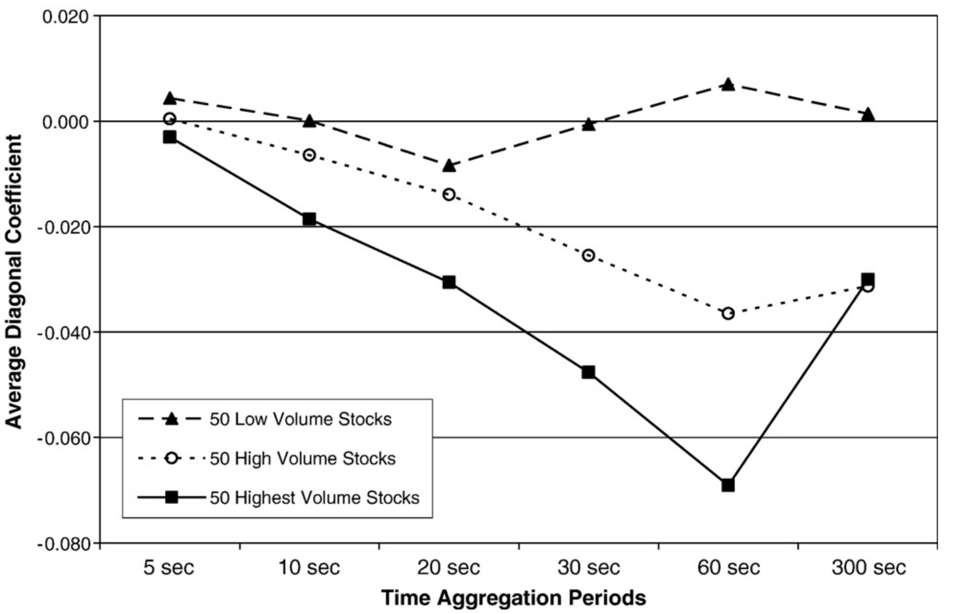

Fig. 2. Average diagonal coefficient for different time aggregations by volume categories.

(30 minute) aggregation interval (results not reported) produces a reliably negative serial correlation in order type consistent with a longer liquidity cycle for low-volume stocks.

5. Conclusion

This paper analyzes the trader's order choice decision under different market conditions for a sample of 148 stocks trading on the NYSE. We estimate a multinomial logit model to test order choice theory. Our main results are: (1) positive serial correlation in order type on an order-by-order basis, which suggests that follow-on order strategies dominate adverse selection or liquidity considerations at a moment in time; (2) aggregated levels of order flow also exhibit positive serial correlation in order type, but appear to be non-stationary processes; (3) changes in aggregated order flow have a serial correlation in order type that starts close to zero at short aggregation intervals, but becomes increasingly negative at longer aggregation intervals. Combining these results, we document a process that simultaneously follows a short-run, order-by-order *centrifugal* process (positive serial correlation) and a long-run, *changes*-in-order-flow *mean-reverting* process (negative serial correlation). The later process implies a liquidity exhaustion–replenishment cycle that accumulates over time and becomes increasingly important. We also find that: (1) small orders routed to an automatic execution system are much less sensitive to quoted spreads than small orders routed to the auction process providing additional support for the speed versus cost trade-off documented in Boehmer (2005); (2) large ask (bid) depth increases the probability of sell (buy) orders supporting a short-term forecast hypothesis; (3) large ask (bid) depth increases the probability of an inside-the-quote limit sell (buy) and decreases the probability of an at-the-quote or behind-the-quote limit sell (buy) supporting a "jump the queue" hypothesis; and (4) aggressively priced limit orders are more likely late in the trading day supporting prior experimental and empirical results consistent with the claim that informed traders switch from demanding to supplying liquidity as the day passes.

As with all empirical studies, several caveats are in order. First, we note that our empirical design captures individual orders, not complete order strategies. Although we adjust for a simple form of order splitting, we cannot anticipate all possible strategies. Second, we have only NYSE electronic order data. Without data from all orders of NYSE-listed securities, we cannot fully characterize order choice. During our sample period 83% of the sample stocks' trades (86% of the volume) occur on the NYSE. We also focus exclusively on electronically submitted (system) orders. We do not have access to orders originally routed to a floor broker instead of the specialist. Finally, it is possible that some brokers internalize or offset incoming orders, suggesting that we see only "net" order flow. Even net order flow, however, is useful in determining shocks to supply and/or demand. Despite these limitations, the richness of our dataset extends our understanding of order dynamics far beyond the insights that trades and quotes datasets such as TAQ alone could generate.

We must exercise caution in claiming to reject theoretical models of order submission strategy. Most theoretical models are cast in a pure limit order book model. Our data come from the NYSE, a hybrid book-floor market. Thus, departures we observe from a model's prediction might be due to departures in the operations of the NYSE compared to a pure limit order book.

Our results have implications for traders and trading venues. Traders demanding liquidity can adapt their order submissions to maximize the likelihood their orders will fill at minimum cost. For example, knowing that it is more likely to observe the arrival of another limit order after observing the arrival of one limit order suggests that potential liquidity demanders might delay slightly in submitting their market order. Likewise, liquidity suppliers can access the competition they are likely to face and the profitability of their orders knowing that order arrivals are serially correlated. Indeed, an extension of this work might use the empirical distribution of order arrivals to derive optimal order submission strategies. Exchange officials and regulators can use these results when suggesting alterations in trading mechanisms and rules. For example, when considering improvements in transparency, an emphasis on information that is useful to liquidity suppliers might prove most beneficial.

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