A Comprehensive Test of Order Choice Theory: Recent Evidence from the NYSE

Andrew Ellul
Indiana University

Craig W. Holden
Indiana University

Pankaj Jain
University of Memphis

Robert Jennings
Indiana University

November 10, 2003

Abstract: We perform a comprehensive test of order choice theory from a sample 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 (floor vs. automatic), and order pricing aggressiveness. We use a multinomial logit specification and a new statistical test. We find a negative autocorrelation in changes in order flow exists over five-minute intervals supporting dynamic limit order book theory, despite a positive first-order autocorrelation in order type. Orders routed to the NYSE's floor are sensitive to market conditions (e.g., spread, depth, volume, volatility, market and individual-stock returns, and private information), but those using the automatic execution system (Direct+) are insensitive to market conditions. When the quoted depth is large, traders are more likely to "jump the queue" by submitting limit orders with limit prices bettering existing quotes. Aggressively-priced limit orders are more likely late in the trading day providing evidence in support of prior experimental results.

JEL Classification Code: G10
Keywords: Order choice, limit order, market order, automatic execution, limit order book

Addresses for correspondence: Andrew Ellul (anellul@indiana.edu), Craig Holden (cholden@ indiana.edu) and Robert Jennings (jennings@indiana.edu) are from the Kelley School of Business, Indiana University, 1309 E. Tenth St., Bloomington, IN 47405-1701. Pankaj Jain (pjain@memphis.edu) is from the Fogelman College of Business, University of Memphis, Memphis, TN 38152.

Acknowledgements: We thank Morgan Stanley & Co., Inc. for financial support and the New York Stock Exchange for providing data. The opinions expressed in this paper do not necessarily reflect those of the employees, members, or directors of the New York Stock Exchange, Inc. We thank Robert Battalio, Joel Hasbrouck, Christine Parlour and seminar participants at Indiana University, the National Bureau of Economic Research Market Microstructure Workshop, the New York Stock Exchange, the Ohio State University, Pennsylvania State University, and Vanderbilt University for useful comments. We are responsible for any errors.

A Comprehensive Test of Order Choice Theory: Recent Evidence from the NYSE

A large theoretical literature on market microstructure develops the trader's optimal order choice under a wide variety of trading mechanisms and market conditions. For example, Parlour (1998) finds that when an order depletes the depth available on a limit order book, the next trader is likely to choose an order replenishing depth (i.e., a market buy order is more likely followed by a limit sell). Thus, she predicts what can be thought of as negative autocorrelation in order type. Handa and Schwartz (1996) model the time that different investors allow themselves to trade and find that impatient traders endogenously choose market orders, whereas patient traders endogenously choose limit orders. By (informal) extension, we posit that extremely impatient traders might choose immediate automatic execution over slower floor execution and that their orders might be submitted virtually irrespective of how favorable or unfavorable the market conditions. Other variables predicted to effect order choice include quoted spread (Cohen, Maier, Schwartz, and Whitcomb 1981; Harris 1998; and Foucault 1999), volatility (Foucault 1999), prior own and market return (Brown and Jennings 1990), and time of day (Harris 1998; Hollifield, Miller, and Sandås 1999; Bloomfield, O'Hara, and Saar 2002).

We provide a comprehensive test of order choice theory. This tests some theories that have not been tested and tests many theories simultaneously. We use NYSE system order data to estimate a multinomial logit model of order choice. We study a wide spectrum of order 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. floor), and the fundamental choice of doing nothing vs. order activity. Our multivariate analysis includes 17 independent variables designed to test theoretical order-choice models. We analyze a several sub-samples and conduct robustness checks. Thus, we obtain a comprehensive and robust set of conclusions about how well actual NYSE order choices conform to what is predicted by theory.

We also provide the first analysis of order choice on the New York Stock Exchange (NYSE) from the era of decimal prices (i.e., penny tick size) and automatic executions via the NYSE's Direct+ system. Recent studies document how profound both of these changes are. Chakravarty, Harris, and Wood (2001) find that switching to decimal prices yields more frequent and smaller quote adjustments, smaller quoted and effective spreads, and smaller depths. In addition, Bacidore, Battalio, and Jennings (2003) find that decimal prices result in a roughly 50% reduction in cumulative depth on the limit order book, smaller order sizes, and more frequent cancellations. Jain (2002) analyzes 118 exchanges around the world and documents that the switch from a pure floor-based system to a combined floor and electronic system results in a lower cost of capital, higher volatility, and more volume. These market structure changes are very likely to impact order choice. Therefore, we believe it is interesting to analyze order choice on the NYSE from the decimal, Direct+ era. This complements prior work on order choice that analyzes the Paris Bourse (Biais, Hillion, and Spatt 1995), NASDAQ (Smith 2000), or 1990-1991 NYSE using the TORQ dataset (Baewho, Jang, and Park 2002; Beber and Caglio 2002).

Order choice is important because it is the foundation of how the NYSE (or any security market) operates. Order submission and cancellation choices are central to the supply of and demand for liquidity. NYSE liquidity is provided by specialists and floor brokers, but public limit 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 Direct+ and OpenBook, have increased 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 SEC 2001b).

One of our findings relates to Biais, Hillion, and Spatt (1995), who use descriptive statistics to demonstrate that the Paris Bourse exhibits *positive* first-order, serial correlation in order type (i.e., a limit sell order is most likely to be followed by another limit sell). This finding is counter to Parlour's theoretical prediction and rather puzzling because it suggests that the limit order book grows more and more imbalanced. We find that the NYSE also exhibits *positive* first-order, order-type serial correlation in 2001. This is true in a multivariate setting where we control for other influences and is quite robust. Biais, Hillon, and Spatt suggest that this result might be an artifact of order-splitting (i.e., a large limit sell is split into a sequence of smaller limit sells). Our dataset identifies the firm and the specific branch within the firm submitting the order. This allows us to identify orders that appear to be split. We adjust the order flow process for order splitting, but still obtain positive first-order, serial correlation in order type. However, when we look at longer time horizons (five minute intervals), we find *negative* serial correlation in *changes* in the order flow processes. The positive order-to-order serial correlation and negative five-minute serial correlation in changes can be reconciled. Both results are consistent with an order flow process that has inertia order-by-order, but slowly mean-reverts. Our finding of a slow mean-reverting order flow process resolves the puzzle of why the limit order book does not continue to become more imbalanced and supports Parlour's theoretical predictions.

Another key finding is that orders sent to Direct+ for automatic execution are much less sensitive to market conditions than orders sent to the floor. In other words, Direct+ orders are submitted with little respect for the previous order type, the current quoted spread or depth, recent volume or volatility, past own or market return, or time of day. This is consistent with the claim that extremely impatient traders choose fast automatic execution no matter what; whereas only moderately impatient traders send their marketable orders to the floor with economically meaningful regard for market conditions.

We have several additional findings. We document that, when the quoted depth is large, traders are more likely to "jump the queue" by submitting limit orders with limit prices bettering existing quotes and less likely to submit orders with limit prices equal to or worse than current quotes. In addition, a favorable (unfavorable) forecast of the rest-of-the-day stock return, as proxied by the realized rest-of-the-day stock return, increases the likelihood of a buy (sell) order. This provides evidence that some traders appear to be effectively exploit private information. If the recent market return is positive (negative), then more buy (sell) orders arrive. This is consistent with momentum-oriented technical trading. We find that order activity is clustered. We find that doing nothing, defined as time passing with-out order activity, also is clustered. Consistent with previous work, we find that wider (narrower) spreads increase the probability of market (limit) orders. However, we find that effect is limited primarily to small orders. Finally, we find that limit orders are more likely late in the trading day, which is inconsistent with the Harris (1998) and Hollifield, Miller, and Sandås (1999) prediction that traders switch from market orders to limit orders late in the trading day. The fact that this result is driven mostly by aggressively-priced orders is consistent with Bloomfield, O'Hara, and Saar (2002) who provide experimental evidence that informed traders switch from demanding liquidity early in the day to provide liquidity late in the day.

To assess the *economic significance* of an explanatory variable's impact on order choice, we calculate what we refer to as an impulse sensitivity. An impulse sensitivity is the change in the estimated probability of the dependent variable caused by a one standard deviation shock in the explanatory variable. To determine the *statistical significance* of the direction of change in the estimated probability, we test the statistical significance of the impulse sensitivities, *not* the statistical significance of the multinomial logit coefficients. To the best of our knowledge, there is no technique in the prior literature to perform such a test, so we develop a test of the statistical significance of the impulse sensitivity.

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. In Section 3, we explain the empirical methodology. Section 4 presents our results. Section 5 concludes. The appendix describes our new test of the statistical significance of an impulse sensitivity.

1. Literature Review and Hypotheses

Last Event. Parlour (1998) develops a model of a transparent limit order book with symmetric information. The probability of executing a limit order depends on the book's state and the trader's patience. Parlour notes that the arrival of a limit buy (sell) order lengthens the queue at the bid (ask) side of the book. This reduces the attractiveness of submitting another limit order of the same kind. Hence, we should observe negative serial correlation in order type.

Last Event Hypothesis: The probability of observing a limit buy (sell) is lowest if the immediately preceding event is a limit buy (sell).[1]

Last Five Minutes. In contrast with Parlour's assumption of full transparency, the NYSE limit order book was closed to off-exchange traders during our sample period. In other words, off-exchange traders might not see the last order before making their order choice. Although marketable orders usually fill and print quickly, specialists have 30 seconds to post limit orders with prices equaling or bettering current quotes and limit orders with limit prices worse than the

[1] All hypotheses are stated as the alternative.

contemporaneous quotes are completely non-transparent to off-floor traders. To give the Parlour model a better chance to predict NYSE order strategy, we aggregate each type of order flow in five-minute intervals and test for serial correlation in changes in the order flow process. The aggregation of order flow in the prior five-minute interval might better represent what a trader not on the floor of the NYSE can consider when submitting an order.[2]

Last Five Minutes Hypothesis: The change in the number of limit buys (sells) over five-minute intervals is lower if the change in the number of limit buys (sells) over the preceding five-minute interval is higher.

Auto-ex vs. Floor. In 2000 the NYSE introduced Direct+; an electronic system that automatically executes small, marketable buy (sell) orders at the quoted ask (bid) price. The size of a Direct+ order is limited to the size of the quote it is trying to hit or 1099 shares, whichever is less. These orders fill within 2 or 3 seconds of arriving at the Exchange and are not eligible for price improvement. By contrast, marketable orders routed to the floor typically take 20 to 40 seconds to execute and often receive price improvement from the floor's oral auction process.

Informally extending the Handa and Schwartz (1996) model, contrast an extremely impatient trader who believes he must trade in only a few seconds to a moderately impatient trader whose believes she must trade within the next one minute. The extremely impatient trader might endogenously choose automatic execution and his order might be submitted with little regard for market conditions. The moderately impatient trader might choose floor execution to get a better price on average and her order might have more regard for market conditions.

Auto-ex Hypothesis: The sensitivity of automatically executed orders to market conditions is less than the sensitivity of floor orders to market conditions.

---

[2] Obviously, there are limitations to how closely the NYSE resembles the theoretical market modeled by Parlour, which limits our ability to test her model precisely.

Spread. Harris (1998) finds that wider spreads increase the cost of demanding liquidity and increase the reward to providing liquidity. This causes the marginal investor to switch from taking liquidity via market orders to supplying it with limits. Alternatively, Foucault (1999) finds that an increase in market volatility makes liquidity demanders less patient, which allows limit order submitters to widen their spread in order to extract greater rents. So, there is a positive relation between spreads and limit orders and a negative relation between spreads and market orders. Biais, Hillion and Spatt (1995), Harris (1998), Hollifield, Miller and Sandås (1999), Smith (2000), Bae, Jang and Park (2002), and Ranaldo (2002) find evidence consistent with this claim. We extend the literature in two ways. First, we test the spread hypothesis differentiating between marketable limit orders and non-marketable limit orders. Second, we test the spread hypothesis differentiating between small, medium, and large orders.

Spread Hypothesis: Narrow (wide) spreads increase the probability of marketable (non-marketable) orders.

Depth. Berber and Caglio (2002) and Ranaldo (2000) analyze the quoted depth's effect on order submission decisions. We extend the literature by investigating whether both sides of the quote seem to affect order choice or if only one side of the quote appears to matter to traders. We also test whether large ask (bid) depth appears to be viewed as forecasting a short-term price decrease (increase), leading to more sells (buys). Finally we test whether 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.

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

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).

Volatility. Foucault (1999) suggests a model of a dynamic limit order market where across-agent variation in the consensus belief about asset valuation leads to a winner's curse problem for traders. With greater volatility, limit orders are placed at less competitive prices as a compensation for the adverse selection risk. Volatility also makes market orders less profitable. In equilibrium, the proportion of limit orders increases when return volatility is high. Although Foucault examines the cross-section of securities, his prediction might be extended to the time-series realm if traders can predict volatility (say, via a GARCH model). Handa and Schwartz (1996) also predict that investors submit more limit orders when volatility rises. Smith (2000), Ahn, Bae, and Chan (2001), Danielsson and Payne (2002), Hollifield, Miller, Sandås and Slive (2002), and Ranaldo (2002) find evidence consistent with a direct relation between security price volatility and limit order arrival frequency. Hasbrouck and Saar (2002), however, find the opposite. In addition, increased volatility in the stock price might be a result of the arrival of valuation-relevant information. If this is the case, then we anticipate that no trading activity is less likely immediately following volatile periods.

Volatility Hypothesis: Higher return volatility is associated with more frequent limit orders and less frequent periods of no trading activity.

Market Return and Own Return. Technical traders use public information reflected in security prices (such as own returns, market returns, etc.) to forecast future price movements. An extensive academic literature analyzes technical trading rules based on past security/market returns (see Brown and Jennings 1990; Gencay 1998; Sullivan 1999; Lo, Mamaysky, and Wang

2000; Ready 2002). It is not unusual for day traders to use minute-by-minute "momentum" or "contrarian" trading strategies.[3] The presence of such traders suggests that there may be short-term patterns to exploit. We allow for this possibility with the following hypothesis.

Market Return Hypothesis: A non-zero market return is associated with changes in order choice.

Own Return Hypothesis: A non-zero own return is associated with changes in order choice.

Time-of- day. In addition to the well-documented U-shaped intra-day pattern in trading activity (e.g. Chung, Van Ness and Van Ness 1999), the economics literature notes a "deadline effect," where agreements are more likely to be reached at the last minute. For example, Roth *et al* (1988) conduct experiments testing for bargaining patterns through time and find that many agreements occur just before the deadline. This suggests that traders become more aggressive as the close of trading approaches. In contrast, Bloomfield, O'Hara and Saar (2002) use an experimental asset market to model traders' behavior in an electronic limit order book. They find that liquidity provision evolves during the trading day. Informed traders demand liquidity early in the trading session by submitting orders that hit existing limit orders but become suppliers of liquidity by submitting more limit orders towards the end of the trading day.

Time of Day Hypothesis: As the close of the trading day approaches, the distribution of order types changes.

We simultaneously test these hypotheses using a multinomial logit model and electronic order data from the New York Stock Exchange.

[3] See many examples in "Risky Business: The Day Traders" in the *Investigate Reports* video series available on the A&E web site (www.aetv.com).

2. Data

We obtain system order data from the NYSE. Because of the 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 two 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.

We use the NYSE's System Order Database (SOD) and its companion quote file (SODQ) to provide an audit trail of system (SuperDOT) orders arriving during the week of April, 30 to May 4, 2001.[4] 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

[4] We have data for April, May, and June for the 148 sample stocks. The large number of order submissions and cancellations makes sampling necessary. We choose this week for our sample period because it appears "typical" of the entire time period in terms of market return and order mix.

time-stamped to the second. System orders represent about 93% of reported NYSE orders and 47% of reported NYSE share volume.[5] Specifically, 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. 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.[6]

Table 1 provides some descriptive statistics for these and other variables.

[Insert Table 1.]

The mean order size is 1,232 shares. Although this is relatively small, we have large orders, as suggested by the maximum order size of 900,000 shares. On average, our sample stocks have 2.24 million shares trading per day, which is a .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 2,760 (3,701) 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 time of an event is 153.76 five-minute intervals past midnight, or approximately 12:48pm. The average five-minute own- and market-return are positive during the sample period. The own-return has more cross-sectional volatility than the market return. The private information variable (measured as the change in the quote midpoint between order arrival time and that day's closing) averages 0.27%.

[5] See SEC (2001a), page 5.
[6] The National Best Bid (Offer) price is the higher (lower) of the NYSE bid (ask) and the best non-NYSE bid (ask).

3. Methodology

3.1. Variables

We analyze the likelihood of observing particular events – the submission of different order types and order cancellations. In addition, because the 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, 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, Kiefer, and O'Hara (1997) use a similar no-activity event to model and estimate the passage of clock time without activity.

Beginning with the first trade of each day, 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 20 seconds and that orders arrive at 9:30:00, 9:30:05, and 9:30:50. There are fewer than 20 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 4:00:00 closing is taken as the end of the trading day.

We distinguish 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 (= .1250 + .1266 + .1641 + .1546). Thus, a cancellation or no-activity event occurs 43% of the time. The fact that limit orders are more frequent than market orders is consistent with extant literature finding that limit orders are more frequent than market orders on the NYSE (e.g., Harris and Hasbrouck, 1996). A simple count of the dependent variables provides a similar mix of events: no-activity events are 32.5% of the observations, cancellations are 14.8%, limit buy orders are 18.0%, limit sell orders are 17.1%, and market buys and sells orders are 8.8% each.

Our analysis differentiates among four types of limit orders: behind-the-quote, at-the-quote, inside-the-quote, and marketable. We place 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 NYSE bid (ask) price. At-the-quote buy (sell) orders have limit prices equal to the NYSE bid (ask) price. Inside-the-quote orders have limit prices between the NYSE bid price and the NYSE ask price. Finally, buy (sell) marketable limit orders have limit prices greater (less) than or equal to the NYSE ask (bid) price.[7] 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 extant theoretical and empirical work on order submission strategy, we identify 17 explanatory variables.[8] We define these variables below.

1. Last event market buy takes the value of 1 if the previous event was a buy market order and 0 otherwise;

2. Last event market sell takes the value of 1 if the previous event was a sell market order and 0 otherwise;

2. Last event limit buy takes the value of 1 if the previous event was a limit buy order and zero otherwise;

4. Last event limit sell takes the value of 1 if the previous event was a limit sell order and zero otherwise;

[7] Peterson and Sirri (2002) provide a more detailed discussion of marketable limit orders.
[8] Using the Belsley, Kuh, and Welsch (1980) method, we do not find a muti-collinearity problem among our explanatory variables.

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. 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; [9]

8. 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);

9. 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);

10. 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;

11. 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;

12. Own return squared is the stock's own return squared;

13. Market return is the percentage change in the quoted spread's midpoint for the exchange traded fund mimicking the S&P500 (SPY) in the five-minute interval prior to the event;

14. Time is the time of day of the event expressed as the number of five-minute intervals since midnight (e.g., 9:30:00am to 9:34:59am is interval 114);

15. Time from noon squared is the deviation of the event's time interval from the mid-day time interval (153) squared;

16. Private information is a measure of the traders' current private information as proxied by the *future* change in stock value. It is calculated as [(closing NYSE quoted spread midpoint) - (order-time NYSE quoted spread midpoint)]/(order-time NYSE quoted spread midpoint); and,

17. 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's equal to zero otherwise.

[9] We obtain similar results if we use both dollar spread and price (or inverse price) in the regressions.

3.2. Models

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

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

In this specification, the subscript "t" represents a contemporaneous value. The subscript "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.[10]

Initially, we analyze a 7-way event structure. The seven events are: (1) cancellation of an existing buy order, (2) cancellation of an existing sell order, (3) the arrival of a Limit Buy order, (4) the arrival of a Limit Sell order, (5) the arrival of a Market Buy order, (6) the arrival of a Market Sell order, or (7) No Activity in a stock-specific time interval since the last event.[11] Next,

[10] 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.
[11] For the 7-way event structure, the "market buy" ("market sell") event includes marketable limit buys (sells), because both types of orders are liquidity-demanding, executable orders. The "limit buy" ("limit sell") event

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) Behind-The-Quote Limit Buy, (4) At-The-Quote Limit Buy, (5) Inside-The-Quote Limit Buy, (6) Marketable Limit Buy, (7) Behind-The-Quote Limit Sell, (8) At-The-Quote Limit Sell, (9) Inside-The-Quote Limit Sell, (10) Marketable Limit Sell, (11) Market Buy, (12) Market Sell, or (13) No Activity (order arrival or cancellation) in a stock-specific time interval since the last event.

4. Results

4.1. Stock-By-Stock Estimation

We estimate equation (1) separately for each stock using all the stock's events.[12] Table 2 reports the results of the 7-way event structure estimation, which ignores limit orders' pricing aggressiveness. Table 3 provides the results of the 13-way event structure, which considers order pricing aggressiveness. Both tables report the mean estimates from the stock-by-stock analysis. In each table, Panel A reports the mean coefficient estimates from the multinomial logit regression and Panel B presents the mean impulse sensitivities. Again, an impulse sensitivity is the change in the probability of a dependent variable (row) caused by a one standard deviation increase in an explanatory variable (column).

To compute the impulse sensitivities reported in Panel B, we define the benchmark probability of each event as the estimated logistic function evaluated at the mean of each of the explanatory variables. In the 7-way analysis, we estimate that the probability of no activity is

---

includes only non-marketable limit orders, because these orders are the liquidity supplying. For expositional clarity, the "market order" vs. "limit order" terminology is used.

[12] For 85 of the sample stocks, we observe all order events during the sample period and find that the maximum likelihood regression converges. We aggregate the data from the remaining stocks in one regression. Thus, for our stock-by-stock analysis, we have 86 observations. Estimating equation (1) with the entire panel of data (i.e., for all stocks simultaneously) gives similar conclusions. We note that the stock-by-stock analysis, with its 86 observations, is a conservative approach to the statistical test compared to the literally millions of observations in the panel regression. Assuming only 86 observations also is conservative to reporting average test statistics from the regressions, which have thousands of observations.

44%, the probability of a limit buy (sell) order of 18% (17%), the probability of a market buy or market sell order is 9%, and the probability of a cancelled order is 3.65%. The 13-way analysis provides similar estimates of the likelihood of cancellations and marketable orders, but estimates that limit orders are less likely (14% for buys and 16% for sells) and no-activity intervals are more likely (49.7%) than the 7-way event model. To compute the change in the probabilities (impulse sensitivities), we successively re-evaluate the estimated logistic function after adding a standard deviation to the mean of one explanatory variable without disturbing the means of the other explanatory variables. Thus, the column labeled "Percent Spread" in Panel B of Tables 2 and 3 reports the impulse sensitivity based on a one standard deviation increase in the percent spread holding all other explanatory variables constant at their mean levels.

Our hypotheses are statements about the impulse sensitivities, so we discuss, interpret, and test the impulse sensitivities, not the coefficient estimates. In most cases, the sign of the multinomial coefficient estimate is the same as that of the impulse sensitivity, but not always.[13] For example, in Table 2 Panel A, the Market Buy coefficient in the Last Limit Sell column is +0.575, but Panel B's Market Buy impulse sensitivity in the Last Limit Sell column is -0.12%. What matters for the multinomial logit coefficients is their *relative size*. In this case, the Market Buy coefficient is smaller than the other coefficients in the Last Limit Sell column, so the Market Buy impulse sensitivity is negative and the other non-base case impulse sensitivities are positive.

Because our hypotheses are concerned with the sign of the impulse sensitivities, we wish to test if an impulse sensitivity is statistically significantly different from zero. There appears to be no established procedure to do this. The appendix derives a new econometric procedure for

[13] They may differ because the multinomial logit coefficients affect the denominator of a probability calculation, as well as the numerator.

testing the statistical significance of an impulse sensitivity. We summarize our hypotheses regarding the expected signs of the impulse sensitivities in Panel C of Table 2.

[Insert Tables 2 and 3.]

Last event. Based on the theoretical work of Parlour (1998) and the empirical work of Bias, Hillion, and Spatt (1995), we are interested in the first-order serial correlations of order types. Consider marketable orders. Examining Table 2, we find that marketable buy (sell) orders are most likely to follow marketable buy (sell) orders. That is, the largest impulse sensitivity in the "Last Market Buy" ("Last Market Sell") column is associated with marketable buy (sell) orders. This is evidence from the marketable order categories of positive serial correlation in order type (a positive diagonal effect). This finding is consistent with the findings in Biais, Hillion, and Spatt (1995) and Yeo (2002) and is inconsistent with the Last Event Hypothesis. A marketable order takes liquidity from the limit order book and produces a shorter queue for new limit orders to stand behind. Parlor (1998) suggests that liquidity suppliers are more willing to join shorter queues. Thus, we expect that marketable orders would be followed by limit orders replenishing the extinguished liquidity (limit sells following market buys and limit buys after market sells). In fact, we find that the likelihood of limit orders arriving on the opposite side of the book from where liquidity was taken increases more after the arrival of a marketable order than the likelihood of a limit order replacing the taken liquidity.

When the previous event is a limit order, the results are equally clear. For limit buy (sell) orders, the likelihood of a limit buy (sell) increases the most. The positive serial correlation from the limit order categories also is inconsistent with the Last Event Hypothesis.[14] Parlour's

[14] As a robustness check on the positive serial correlation in order type findings, we check two alternative specifications. First, we estimate the same 7-way event structure but drop the spread, bid depth, and ask depth explanatory variables. Second, we estimate the same 7-way event structure but drop the spread, bid depth, ask depth, volume, and volatility explanatory variables. Our thought was that perhaps these highly transparent (to off-floor

predictions do not seem to hold on an order-by-order basis. Table 3 confirms that the arrival of a limit buy (sell) order increases the likelihood of seeing another non-marketable limit buy (sell) order for all levels of pricing aggressiveness except (including) marketable orders.

Finally, we examine the changes in probabilities conditional on an order's cancellation. Our results are consistent with a trader canceling existing limit orders and submitting new ones. When a buy (sell) order is cancelled, the most likely subsequent event is the arrival of a new buy (sell) limit order. Table 3 indicates that the increase in likelihood of non-marketable limit orders is common across all levels of pricing aggressiveness.

Activity and No Activity. We see that most of the impulse sensitivities associated with the last event variables are positive. This suggests that order activity is clustered – the arrival or cancellation of any type of order significantly increases the likelihood of additional order activity and decreases the likelihood of no activity.

No activity is also 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, the likelihood of a subsequent no-activity interval increases. Thus, we extend the Bias, Hillion, and Spatt (1995) diagonal effect to no activity intervals as well.

Percentage spreads. In Table 2, we find that wide spreads increase the probability of non-marketable orders and decrease the probability of marketable orders. This is consistent with the Spread Hypothesis and with prior findings by Biais, Hillion and Spatt (1995), Harris (1998), Hollifield, Miller and Sandås (1999), Smith (2000), Bae, Jang and Park (2002), and Ranaldo (2002). In Table 3, we extend the literature by finding that wide spreads lower the probability of marketable limit orders, just like market orders. Whereas, wide spreads increase the probability

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 every bit as strong in these two alternative specifications.

of on inside-the-quote and at-the-quote orders limit orders and marginally reduced the probability of behind-the-quote limit orders. In other words, marketable limit orders respond to the spread more like market orders than non-marketable limit orders. In a later section, we test the spread hypothesis for small, medium, and large orders.

Depth. Table 2 shows that the 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 both a limit sell (buy) and a market sell (buy). This supports the Short-Term Forecasting Hypothesis.

Table 3 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.

Trading Volume. Generally, elevated trading volume in the prior five-minute interval is associated with more contemporaneous trading activity (less frequent no-activity events). That is, order activity has positive serial correlation. This is consistent with the Volume Hypothesis. The relative magnitudes of the probability changes suggest that much of this activity is new, not replacement, orders. That is, the increased likelihood of a new limit order is greater than the increased likelihood of an order cancellation.

Own return. We find support for the Own Return Hypothesis in Table 2. Own return in the previous five-minute interval is positively correlated with the frequency of buy orders and negatively correlated with the likelihood of sell orders. Thus, there appears to be short-term "momentum" trading; buying (selling) as the price increases (decreases). For limit orders, some of this might be mechanical refilling of the bid (ask) side of the limit order book after a price increase (decrease).

Volatility. Squaring own-return provides an estimate of the time-series price volatility. We find that lagged volatility is associated with an increased probability of all order activities. The increase in non-marketable limit order probability in Table 2 is large relative to the increase in marketable order likelihood, which is weakly consistent with the Volatility Hypothesis.[15] Table 3 suggests that the increased likelihood of non-marketable limit orders is focused on at- and behind-the-quote orders. Thus, traders tend not to narrow spreads after volatile periods.

Market return. After controlling for the security's own return, the return on the market (S&P 500 Exchange Traded Fund) in the prior five-minute interval increases the likelihood of buy orders and decreases the likelihood of sell orders, providing support to the Market Return Hypothesis. This is consistent with the idea that a trader views the market return as a leading indicator for a security's short-term price change. The effect on non-marketable limit orders detailed in Table 3 suggests that traders become more aggressive on the bid side (increasing the likelihood of at- and inside-the-quote orders) and less aggressive on the offer side when the return on the market in the previous five minute interval is positive.

Time-from-noon Squared. The time-from-noon-squared variable is large when events occur early or late in the day. This controls for the documented (e.g., Chung, Van Ness and Van Ness, 1999) U-shaped intra-day trading pattern. In Table 2, all events' impulse sensitivities associated with an increase in *Time Squared* are positive. This suggests that all order types and cancellations are more frequent early and late in the trading day. This is consistent with a U-shaped trading pattern. Not surprisingly, the no-activity event is less likely early or late in the

[15] Because the likelihood of order cancellation also increases in volatility, many of the limit orders might be replacement orders. It is not obvious that Foucault (1999) makes time series predictions regarding volatility. Hasbrouck and Saar (2002) do not support the predictions of Foucault in the cross-section.

trading day. Table 3 shows that the U-shaped intra-day pattern is less pronounced for at- and inside-the-quote limit orders.

Time-of-day. After controlling for the U-shaped intra-day pattern in trading activity, the time-of-day is not significantly positively associated with the likelihood of cancellations or with the probability of marketable order arrivals. This is inconsistent with the hypothesis that a trader converts from limit orders to market orders during the trading day as they become less patient toward the close of trading (e.g., Harris, 1998). However, we find 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, O'Hara, and Saar (2002), that finds that informed traders demand liquidity early in the day but later assume the role of market maker.

Private information. Although own return and market return in the previous five-minute interval might control for public information arriving in the market, we also might wish to control for current private information that has not yet been reflected in the security's price. Our forward-looking, private information proxy is the change in the spread's midpoint between an orders' arrival and day's end. The impulse sensitivities associated with buy orders are positive and the impulse sensitivities associated with sell orders are negative. This suggests that as the value of the private information variable increases (meaning that there is favorable private information) the fraction of buy orders in total order flow increases. Conversely, when the private information variable suggests unfavorable private information, then the portion of sell orders in the total order flow increases. Private information appears to particularly affect the likelihood of at- and inside-the-quote non-marketable limit orders and marketable orders.[16]

[16] As a robustness check, we drop the "look-ahead" private information variable and re-estimate the 7-way event structure and the 13-way event structure. The non-reported results do not change our conclusions with respect to other variables.

NYSE not at the NBBO. It is possible that traders behave differently when the NYSE quote is not at the NBBO than when it is. For example, when the NYSE is not at the NBBO, then a limit order which merely matches the NBBO will get you first in line on the NYSE. Thus, we expect more inside-the-quote limit orders when the NYSE is not at the NBBO. Looking at Table 3, Panel B, we observe an increased probability of inside-the-quote limit orders when the NYSE is not at the NBBO. We also see an increase in cancellation activity. This supports that idea that traders rationally increase their provision of liquidity when there is a competitive opportunity to do so.

4.2. The Order Flow Process Over Longer Horizons

Parlour (1998) assumes full transparency of the limit order book, but off-exchange traders do not have access to the NYSE limit order book during our sample period. To give the Parlour model a fairer test, we analyze order choices aggregated over longer time intervals. As a starting point, consider a simple plot of aggregate buys and aggregate sells over five-minute intervals. Figure 1 shows the total number of buy orders (solid diamonds) and sell orders (empty squares) submitted in five minute intervals for 148 stocks by time of day on April 3, 2001. A quadratic function (solid curve) has been fitted to the data by choosing the quadratic parameters to minimize the sum of squared errors.

[Insert Figure 1.]

We find a U-shaped pattern in order arrival over the trading day similar to what others have found for volume and volatility. 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%.

Turning to a multivariate analysis, we estimate a new version of equation (1) aggregated over five-minute intervals. To do this we define an order flow process for each order type (market buy, market sell, limit buy, limit sell, cancel buy, cancel sell) or no activity event by counting the number of orders/events during five-minute intervals throughout the trading day. The new dependent variables are the change in the number of orders/events for a given stock over a five-minute interval compared to the previous five-minute interval. Similarly, the new version of the "Last Event" variables are "Last Five Minute" explanatory variables, defined as the change in the number of orders/events for a given stock over the last five-minute period compared to the lag-two five-minute period. In the same spirit, the new version of spread, bid size, and ask size are the average spread, average bid size, and average ask size over the five-minute interval. NYSE at the BBO becomes the fraction of the five-minute interval that the NYSE quoted prices match *both* the best bid and the best offer.

We estimate the new version of equation (1) with Ordinary Least Squares (OLS). In Panel A, we report estimated OLS regression coefficients, where each row is one regression. In Panel B, we report economic sensitivities. An economic sensitivity is the change in the number of orders/events caused by a one standard deviation shock in the explanatory variable. The **bold numbers** are significant at the 1% level based on a standard t-test. Since we are aggregating by five-minute intervals, the sample size is reduced to 11,398.

[Insert Table 4.]

We find that the five-minute order flow process has very different properties than the order-by-order process. None of the coefficients for percent spread, relative bid size, relative ask size, relative volume, or time squared are statistically significant or economically significant. Most of the Last Five Minute coefficients are both statistically significant and economically significant. Looking down the Panel A diagonal of the Last Five Minute coefficients, we see that all of the estimated correlation coefficients are negative (e.g. Last Cancel Buy has a -0.41 coefficient with Cancel Buy) and statistically significant. All of the off-diagonal coefficients are positive or less negative than the diagonal coefficients. Turning to Panel B, we see that the economic sensitivities of the Last Five Minute variables tend to be much larger in absolute value than the economic sensitivities of the other explanatory variables. All of the diagonal terms have large negative economic sensitivities. All of the off-diagonal economic sensitivities are positive or less negative than the diagonal economic sensitivities. Overall, this is a strong evidence of a *negative* serial correlation in changes in the order flow process (that is, a *negative* diagonal effect). It is both statistically and economically significant. This supports the Last Five Minutes Hypothesis and strongly supports the Parlour model.

How can the order-by-order results and the five-minute results be reconciled? First, it is not unusual to have very different patterns at different levels of time aggregation. For example, stock returns exhibit *negative* serial correlation on a minute-by-minute basis due to bid-ask bounce (see Jegadeesh 1990 and Lehmann 1990), *positive* serial correlation over 3- to 12-month holding periods (see Jegadeesh and Titman 1993 and Rouwenhorst 1998), and *negative* serial correlation over 3- to 5-year holding periods (see DeBondt and Thaler 1985). Second, the order-by-order results and five-minute results *both* are consistent with order flow processes that are slowly mean-reverting. The five-minute *negative* serial correlation in changes causes the *level* of the process to mean-revert, which drives the process back towards long-run balance. In other words, we find that the economic forces analyzed by Parlour control the longer-term, five-minute dynamics, which tend to maintain the longer-term equilibrium.

4.3. Separating Auto-ex Orders from Floor Orders

In Table 5, we separately consider orders routed to the automatic execution system (Direct+) and orders routed to the floor. Specifically, the marketable order types are subdivided into auto-ex or floor. Thus, we estimate a 9-way event model: (1) cancel buy; (2) cancel sell; (3) limit buy order; (4) limit sell order; (5) floor marketable buy; (6) floor marketable sell; (7) auto-ex marketable buy; (8) auto-ex marketable sell; and, (9) no activity. We pool data across stocks for this regression. Due to the large number of observations with this approach, all of the impulse sensitivities are statistically significant.

[Insert Table 5.]

Panel A shows the impulse sensitivities for the 9-way event model. The most striking result is that the impulse sensitivities of the auto-ex orders are much smaller than those of the floor orders. To see how much smaller they are, Panel B shows the value of the floor impulse sensitivity relative to the auto-ex impulse sensitivity. The median ratio for marketable buys is 69 and the median ratio for marketable sells is 140. Auto-ex orders are very insensitive to market conditions; whereas floor orders have economically meaningful regard for market conditions. This supports the proposition that extremely impatient traders submit auto-ex orders, whereas moderately impatient traders submit marketable floor orders.

4.4 Robustness

As one robustness check, we re-estimate the 7-way event structure and the 13-way event structure using data from the first day of our sample (April 3) and again using the last day of our sample (June 27). These results, which we do not report, are strongly similar to the results in Tables 2 and 3.[17] In all of the reported robustness checks below, we re-estimate equation (1)

[17] We also perform a non-reported robustness check for potential endogeneity problems. It is possible that contemporaneous volume, quotes and volatility might be co-determined. To address this we use an instrument for

using pooled data. That is, we do not estimate equation (1) separately for each stock. Our pooled regression has sufficient observations so that all regression coefficients and impulse sensitivities are different from zero at traditional significance levels. Therefore, we do not report significance levels. We only discuss when the conclusions differ from the results presented in the previous section. In order to save space, we report only the impulse sensitivities.

4.4.1 Order Size

Table 6 provides the impulse sensitivities resulting from re-estimating equation (1) conditional on the size of the order. We arbitrarily construct three order-size categories. Small orders are defined as orders of fewer than 1,000 shares. Medium orders range between 1,000 and 9,999 shares. Large orders exceed 9,999 shares. We pool (across stocks) all orders in the given size categories for each re-estimation.

[Insert Table 6.]

An interesting finding comes from testing the spread hypothesis by order size. We find that a wide spread greatly increases (decreases) small limit (market) orders, moderately increases (decrease) medium limit (market) orders, but has little effect on large limit (market) orders. This is probably because a large order size dwarfs the quoted depth and so the quoted spread is a far less relevant predictor of trading cost for these orders. In general, we note that most of the impulse sensitivities are smaller for large orders. This is especially true for large limit orders.

4.4.2 Volume and Price Level

Recall that 100 of our sample securities are selected to provide cross-sectional dispersion across trading volume and security price. As a robustness check, we re-estimate the logit model conditioning on volume and price. Table 7 shows these results. Panel A pools the data from the

---

the volume in the previous five-minute interval. The instrument we use is the volume in the five-minute interval prior to the previous five-minute interval (i.e., t-2). This alternative specification does not alter our conclusions in any meaningful manner.

50 most active stocks. Panel B's (C's) impulse sensitivities result from examining the high-volume:high-priced (:low-priced) stocks. Finally Panel D pools the low-volume stocks' data. Pooling all 50 low volume stocks is necessary to obtain convergence of the maximum likelihood estimation of equation (1).

[Insert Table 7.]

Although the results generally are strongest for the higher volume subsets, most conclusions are consistent across the various volume-price groups. A few exceptions are evident. For the low-volume stocks, we find that 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 to sloppy executions in difficult markets. The Volatility Hypothesis (of Foucault, 1999) is supported for the low-volume stocks. In addition, the likelihood of limit buy (sell) orders increases (decreases) as the market return from the previous five-minute interval increases for the low price and lowest-volume stocks. For the lowest-volume stocks, there is some evidence consistent with the claim that traders switch from limit to market orders as the day passes. Finally, the largest impulse sensitivity with the Last Event Market Buy (Sell) is associated with limit buy (sell) orders in all but the highest volume stocks, suggesting that as liquidity is extinguished on one side of the book liquidity is added on the opposite side.

4.4.3 Order Splitting and End-of-Day Effects

We perform additional robustness checks on the 7-way event structure and report the results in Table 8. We allow for the possibility that traders split orders in Panel A, and determine if differences in order choice emerge toward the close of the trading day in Panel B.

[Insert Table 8.]

Order Splitting. A trader can decide to divide the original order into several, smaller orders if that appears optimal. Using the raw data, we might misestimate the coefficients because we treat each order as a separate trading decision when, in fact, one decision might result in several orders. This is particularly true of the impulse sensitivities associated with the Last Event variables. We control for order splitting by developing an algorithm to identify similar successive orders submitted in close proximity to one another. Our data identify the member firm submitting the order as well as the branch office from which the order is submitted. We assume that consecutive orders originating from the same branch of the same broker on the same side of the market as the prior order are split orders. To address this potential problem, we keep the first order in a series of consecutive "identical" orders and delete the successive orders as the outcome of order splitting. We experiment with deleting from one to fifteen successive identical orders. In this paper, we report results from examining fifteen successive orders.[18]

We re-estimate the logit model after eliminating "duplicate" orders. The results are in Panel A of Table 8. Except for minor differences in some impulse sensitivities associated with quoted size and own return, there are no major departures from the results discussed above. In particular, the positive first-order serial correlation in order type is maintained.

Orders Near the Close. Cushing and Madhavan (2000) find that there is a higher demand for immediacy at the close of trading than during the day. Although our "Time" and "Time-from-noon-squared" variables address time-of-day effects, we re-estimate equation (1) using only orders submitted in the final 15 minutes of the trading day. This reduces our sample size to 227,399 events. Our results, reported in Panel B of Table 8, suggest some differences in order

[18] Note that we are not attempting to control for all possible order splitting strategies. We simply are trying to determine whether 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. Traders might split orders among multiple execution venues. This also suggests that we might not fully characterize order splitting strategies.

choice. The impulse sensitivities associated with our quoted size variables indicate that traders appear less willing to join a queue when the end of trading is near. When bid (ask) size is large, traders are less likely to submit buy (sell) limit orders. There also is less evidence of momentum trading in the last 15 minutes of trading. Finally, the time and time squared variables suggest less trading at the end of our 15-minute interval than at the beginning.[19]

5. Conclusion

This paper analyzes the trader's order choice decision across different securities and under different market conditions for a sample of 148 stocks trading on the NYSE. We estimate a multinomial logit model of order choice to perform a comprehensive test of order choice theory. Our main results are: (1.) negative autocorrelations in changes in the order flow processes over five minute intervals supporting dynamic limit order book theory, despite positive first-order autocorrelation in order type; (2.) orders routed to an automatic execution system are much less sensitive to market conditions than orders routed to the floor supporting an extreme impatience theory of automatic execution customers; (3.) wider (narrower) spreads increase the probability of small limit (marketable) orders, but have a negligible effect on large limit (marketable) orders; (4.) large ask (bid) depth increases the probability of sells (buys) supporting a short-term forecast hypothesis; (5.) 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; (6.) favorable (unfavorable) forecasts of the rest-of-the-day stock return increase the likelihood of buy (sell) orders providing direct evidence of effective private information trading; (7.) positive (negative) last-five-minute market returns generate more buy (sell) orders indicating momentum-oriented technical trading; (8.) order activity is clustered; (9.) doing nothing, defined as the passage of time without order

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

activity, is clustered; and (10.) aggressively priced limit orders are more likely late in the trading day providing evidence in support of prior experimental results.

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. We also note that all strategies are not equally available to all traders. For example, the model might suggest that an order be cancelled, but we cannot observe that outcome if an order has not been previously placed. Third, we have only NYSE order data. Without data from all venues trading NYSE-listed securities, we cannot fully characterize order choice. During our sample period 83% of the sample stocks traders (86% of the volume) occurred on the NYSE. Finally, we focus exclusively on electronically-submitted (system) orders. We do not have access to most orders originally routed to a floor broker instead of the specialist.

Our results have implications for traders, trading venues, and regulators. Traders that demand liquidity can adapt their order submissions to maximize the likelihood their orders will fill at minimum cost. Liquidity suppliers can access the competition they are likely to face and the profitability of their orders. Exchange and regulators can use these results when suggesting alterations in trading mechanisms and rules.

Appendix: Testing The Statistical Significance of an Impulse sensitivity

Let $\hat{\boldsymbol{\pi}}$ be a vector of unrestricted reduced form parameter estimates and $\boldsymbol{\Psi}$ be the covariance matrix of the parameter estimates $\hat{\boldsymbol{\pi}}$. Let $\mathbf{h}(\boldsymbol{\pi})$ be a r-dimensional set of r restrictions, which are nonlinear in $\boldsymbol{\pi}$, and $\mathbf{H} = \partial \mathbf{h}(\boldsymbol{\pi})' / \partial \boldsymbol{\pi}$. For a sample size T, the Wald test statistic

$$q = T\mathbf{h}(\hat{\boldsymbol{\pi}})' (\mathbf{H}'\boldsymbol{\Psi}\mathbf{H})^{-1} \mathbf{h}(\hat{\boldsymbol{\pi}})$$

is asymptotically $\chi^2_{(r)}$ and is asymptotically equivalent to a likelihood ratio test (see Byron, 1974 and Judge et al, 1985, pgs 615-616).

We apply the Wald technique to calculate the statistical significance of an impulse sensitivity, where the unrestricted reduced form parameter estimates arise from a multinomial logit. An impulse sensitivity is the change in probability of a particular dependent variable caused by a one standard deviation shock in an independent variable.

Let $i = 1, 2, \ldots, I$ index the dependent variables, *excluding the base case variable*. Let $j = 1, 2, \ldots, J$ index the independent variables, including the intercept. Stack the $I \ x \ J$ reduced form estimated coefficients into a (1xIJ) vector $\mathbf{c}$ in ji order.[20]

Let a_j and b_j be the mean and standard deviation of the j^{th} independent variable.[21] Insert these values into (1xIJ) vectors to create I vectors $\mathbf{m_i}$ and IJ vectors $\mathbf{s_{ji}}$ as shown below. For example, here are $\mathbf{m}_1$, $\mathbf{m}_2$, $\mathbf{s}_{11}$, $\mathbf{s}_{21}$, $\mathbf{s}_{12}$, and $\mathbf{s}_{22}$

[20] The ji order matches the SAS ordering of outputs from a multinomial logit.
[21] As one of the dependent variables, the intercept has a mean of 1 and a standard deviation of 0.

$$\mathbf{m}_1 = \left[\begin{array}{c} a_1 \\ 0 \\ 0 \\ 0 \\ \hline a_2 \\ 0 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right] \quad \mathbf{m}_2 = \left[\begin{array}{c} 0 \\ a_1 \\ 0 \\ 0 \\ \hline 0 \\ a_2 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right] \begin{array}{l} \left.\begin{array}{c} \\ \\ \\ \\ \end{array}\right\} \begin{array}{l} I \text{ elements in} \\ \text{each partition} \end{array} \\ \\ J \text{ partitions} \\ \\ \\ \end{array} \quad \mathbf{s}_{11} = \left[\begin{array}{c} a_1 + b_1 \\ 0 \\ 0 \\ 0 \\ \hline a_2 \\ 0 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right] \quad \mathbf{s}_{21} = \left[\begin{array}{c} a_1 \\ 0 \\ 0 \\ 0 \\ \hline a_2 + b_2 \\ 0 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right] \quad \mathbf{s}_{12} = \left[\begin{array}{c} 0 \\ a_1 + b_1 \\ 0 \\ 0 \\ \hline 0 \\ a_2 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right] \quad \mathbf{s}_{22} = \left[\begin{array}{c} 0 \\ a_1 \\ 0 \\ 0 \\ \hline 0 \\ a_2 + b_2 \\ 0 \\ 0 \\ \hline \vdots \end{array}\right].$$

We insert the first mean, a_1, in the 1st element of the first partition of $\mathbf{m}_1$, the second mean, a_2, in the 1st element of the second partition of $\mathbf{m}_1$, and so on for all J partitions. Similarly, into all of the $\mathbf{m_i}$ vectors, we insert the means in the ith element of each partition. We construct $\mathbf{s}_{11}$ identically to $\mathbf{m}_1$, except that we insert the shock b_1 into the 1st element of the first partition only. Similarly, all of the $\mathbf{s_{ji}}$ vectors are identical to the corresponding $\mathbf{m_i}$ vector, except that they add the shock b_j only to the ith element of the jth partition.

Let p_{ji}^m be the jith probability evaluated at the means of the dependent variables. Let p_{ji}^s be the jith probability evaluated at the mean plus the one standard deviation shock for the jth dependent variable and at the means of the other dependent variables. Let Δp_{ji} be the jith change in probability, which is calculated as

$$\Delta p_{ji} \equiv p_{ji}^s - p_{ji}^m = \frac{\exp\left(\mathbf{c}'\mathbf{s_i}\right)}{1 + \sum_{k=1}^{I} \exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)} - \frac{\exp\left(\mathbf{c}'\mathbf{m_i}\right)}{1 + \sum_{k=1}^{I} \exp\left(\mathbf{c}'\mathbf{m_k}\right)}.$$

Let $\partial \Delta p_{ji} / \partial \mathbf{c}$ be a (IJ x1) vector of partial derivatives. Using the quotient rule, we get

$$\frac{\partial \Delta p_{ji}}{\partial \mathbf{c}} = \frac{\mathbf{s_{ji}} \cdot \exp\left(\mathbf{c}'\mathbf{s_{ji}}\right)\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)\right\} - \exp\left(\mathbf{c}'\mathbf{s_{ji}}\right)\left\{\sum_{k=1}^{I}\mathbf{s_{jk}} \cdot \exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)\right\}}{\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)\right\}^2}$$

$$- \frac{\mathbf{m_i} \cdot \exp\left(\mathbf{c}'\mathbf{m_i}\right)\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{m_k}\right)\right\} - \exp\left(\mathbf{c}'\mathbf{m_i}\right)\left\{\sum_{k=1}^{I}\mathbf{m_k}' \exp\left(\mathbf{c}'\mathbf{m_k}\right)\right\}}{\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{m_k}\right)\right\}^2}.$$

We test a single $\left(r=1\right)$, cross-equation restriction $\Delta p_{ji} = 0$. Using the covariance matrix $\mathbf{\Psi}$[22] of the reduced form parameter estimates $\mathbf{c}$ with a sample size of T, the Wald test statistic

$$q = T\left(\Delta p_{ji}\right)\left(\frac{\partial \Delta p_{ji}}{\partial \mathbf{c}}' \mathbf{\Psi} \frac{\partial \Delta p_{ji}}{\partial \mathbf{c}}\right)^{-1}\left(\Delta p_{ji}\right)$$

is asymptotically distributed $\chi^2_{(1)}$.

For the base case dependent variable, the j[th] change in probability is

$$\Delta p_j \equiv p_j^s - p_j^m = \frac{1}{1+\sum_{\mathbf{l}=1}^{I}\exp\left(\mathbf{c}'\mathbf{s_{jl}}\right)} - \frac{1}{1+\sum_{\mathbf{l}=1}^{I}\exp\left(\mathbf{c}'\mathbf{m_l}\right)}.$$

For the base case dependent variable, the (IJ x1) vector of partial derivatives $\partial \Delta p_j / \partial \mathbf{c}$ is

$$\frac{\partial \Delta p_j}{\partial \mathbf{c}} = \frac{-\sum_{k=1}^{I}\mathbf{s_{jk}} \cdot \exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)}{\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{s_{jk}}\right)\right\}^2} + \frac{\sum_{k=1}^{I}\mathbf{m_k}' \exp\left(\mathbf{c}'\mathbf{m_k}\right)}{\left\{1+\sum_{k=1}^{I}\exp\left(\mathbf{c}'\mathbf{m_k}\right)\right\}^2}.$$

For the single restriction $\Delta p_j = 0$ using the same covariance matrix $\mathbf{\Psi}$, the Wald statistic

$$q = T\left(\Delta p_j\right)\left(\frac{\partial \Delta p_j}{\partial \mathbf{c}}' \mathbf{\Psi} \frac{\partial \Delta p_j}{\partial \mathbf{c}}\right)^{-1}\left(\Delta p_j\right)$$

is asymptotically distributed $\chi^2_{(1)}$.

[22] See Maddala (1999), page 37 for details on how to calculate the covariance matrix $\mathbf{\Psi}$ in a multinomial logit.

References

Ahn, H., K. Bae, and K. Chan, 2001, "Limit Orders, Depth, and Volatility," *Journal of Finance* 56, 767-88.

Bae, K-H., H. Jang, and K. Park, 2002, "Traders' Choice between Limit and Market Orders: Evidence from NYSE Stocks," *Journal of Financial Markets*, forthcoming.

J. Bacidore, R. Battalio, and R. Jennings, 2003, "Order Submission Strategies, Liquidity Supply, and Trading in Pennies on the New York Stock Exchange," *Journal of Financial Markets* 6, 337-362.

Belsley, D. A., E. Kuh, and R. E. Welsch, 1980, Regression Diagnostics, Wiley Publishing, New York.

Beber, A., and C. Caglio, 2002, "Orders Submission Strategies and Information: Empirical Evidence from the NYSE," unpublished paper, University of Pennsylvania.

Biais, B., P. Hillion, and C. Spatt, 1995, "An Empirical Analysis of the Limit-order Book and the Order Flow in the Paris Bourse," *Journal of Finance* 50, 1655-89.

Bloomfield, R., M. O'Hara, and G. Saar, 2002, "The 'Make or Take' Decision in an Electronic Market: Evidence on the Evolution of Liquidity," Unpublished paper, Cornell University.

Brown, D. and R. Jennings, 1990, "On Technical Analysis," *Review of Financial Studies* 2, 527-552.

Byron, R. P., 1974, "Testing Structural Specification Using the Unrestricted Reduced Form," *Econometrica*, 42, 869-84.

Chung, K., B. Van Ness, and R. Van Ness, 1999, "Limit Orders and the Bid-Ask Spread," *Journal of Financial Economics* 53, 255-87.

Cohen, K., S. Maier, R. Schwartz, and D. Witcomb, 1981, "Transactions Costs, Order Placement Strategy, and Existence of the Bid-Ask Spread," *Journal of Political Economy* 89, 287-305.

Cushing, D., and A. Madhavan, 2000, "Stock Returns and Trading at the Close," *Journal of Financial Markets* 3, 45-62.

Danielsson, J., and R. Payne, 2002, "Measuring and Explaining Liquidity on an Electronic Limit Order Book: Evidence from Reuters D2000-2," unpublished paper, Financial Markets Group, London School of Economics.

De Bondt, W. and R. Thaler, 1985, "Does the Stock Market Overreact?" *Journal of Finance* 40, 793–805.

Easley, D., N. Kiefer, and M. O'Hara, 1997, "One Day in the Life of a Very Common Stock," *Review of Financial Studies*, 10, 805-35.

Ellul, A., C. Holden, P. Jain, and R. Jennings, 2003, "Optimal Intertemporal Order Strategy," Indiana University working paper.

Foucault, T., 1999, "Order Flow Composition and Trading Costs in a Dynamic Limit Order Market," *Journal of Financial Markets* 2, 99-134.

Gencay, R., 1998, "The Predictability of Security Returns With Simple Technical Trading Rules," *Journal of Empirical Finance* 5, 347-359.

Handa, P., and R. Schwartz, 1996, Limit Order Trading, *Journal of Finance* 51, 1835-61.

Harris, L., 1998, "Optimal Dynamic Order Submission Strategies in Some Stylized Trading Problems," *Financial Markets, Institutions, and Instruments* 7, 1-75.

Harris, L., and J. Hasbrouck, 1996, "Market versus Limit Orders: the SuperDOT Evidence on Order Submission Strategy," *Journal of Financial and Quantitative Analysis* 31, 212-31.

Hasbrouck, J., and G. Saar, 2002, "Limit Orders and Volatility in a Hybrid market: The Island ECN," unpublished paper, New York University.

Hollifield, B., R. Miller, and P. Sandås, 1999, "An Empirical Analysis of Limit Order Markets," Unpublished paper, Rodney White Center for Financial Research Working Paper 029-99, University of Pennsylvania.

Hollifield, B., R. Miller, P. Sandås, and J. Slive, 2002, "Liquidity Supply and Demand in Limit Order Markets," Unpublished paper, Rodney White Center for Financial Research Working Paper, University of Pennsylvania.

Jegadeesh, N., 1990, "Evidence of Predictable Behavior of Security Returns," *Journal of Finance* 45, 881–98.

Jegadeesh, N. and S. Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Market Efficiency," *Journal of Finance* 48, 65–92.

Judge, G.G., W.E. Griffiths, R.C. Hill, H. Lutkepohl, and T.C. Lee, 1985, *The Theory and Practice of Econometrics*, John Wiley and Sons, New York.

Kavajecz, K., 1999, "A Specialist's Quoted Depth and the Limit Order Book," *Journal of Finance* 54, 747-72.

Lehmann, B., 1990, "Fads, Martingales, and Market Efficiency," *Quarterly Journal of Economics* 105, 1–28.

Lo, A., H. Mamaysky, and J. Wang, 2000, "Foundations of Technical Analysis: Computational Algorithms," *Journal of Finance* 55, 1705-1765.

Maddala, G.S., 1999, *Limited-Dependent and Qualitative Variables in Econometrics*, Cambridge University Press, Cambridge.

Parlour, C., 1998, "Price Dynamics in Limit Order Markets," *Review of Financial Studies* 11, 789-816.

Peterson, M., and E. Sirri, 2000, "Order Submission Strategy and the Curious Case of Marketable Limit Orders," *Journal of Financial and Quantitative Analysis* 37, 221-41.

Ranaldo, A., 2002, "Order Aggressiveness in Limit Order Book Markets," *Journal of Financial Markets*, forthcoming.

Ready, M., 2002, "Profits from Technical Trading Rules," *Financial Management* 31, 43-61.

Roth, A., K. Murnigham, and F. Schoumaker, 1988, "The Deadline Effect in Bargaining: Some Experimental Evidence," *American Economic Review* 78, 806-23.

Rouwenhorst, G., 1998, "International Momentum Strategies," *Journal of Finance* 53, 267–84.

Sandås, P., 2001, "Adverse Selection and Competitive Market Making: Empirical Evidence from a Pure Limit Order Market," *Review of Financial Studies* 14, 705-34.

Seppi, D., 1997, "Liquidity Provision with Limit Orders and a Strategic Specialist," *Review of Financial Studies* 10, 103-50.

Smith, J., 2000, "Market versus Limit Order Submission Behavior at a Nasdaq Market Maker," Unpublished paper, Nasdaq Economic Research.

Sullivan, R., A. Timmerman, and H. White, 1999, "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap," *Journal of Finance* 54, 1647-1691.

Swinscow, T., 1997, *Statistics at Square One*, 9th edition, London, BMJ Publishing.

United States Securities and Exchange Commission, 2001, Report on Comparison of Order Executions Across Equity Market Structures, Office of Economic Analysis.

United States Securities and Exchange Commission, 2001, "Disclosure of Order Execution and Routing Practices."

Yeo, W., 2002, “Persistent Pattern in Limit Order Submission,” unpublished paper, Indiana University.

Table 1. Descriptive Statistics

The 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 five minutes prior to the order arrival or cancellation. Market return is the change in the midpoint of the midpoint of the bid-ask spread of the exchange traded fund representing the Exchange Traded Fund tracking the S&P500 Index. Private information variable is measured as [(closing quote midpoint) - (order-time quote midpoint)/(order-time quote midpoint)].

Variable	**Mean**	**Std. Deviation**	**Minimum**	**Maximum**
Order size	1,231.88	5,501.62	100	900,000
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
Time	153.76	24.52	114	192
Own Return	0.000141	0.009252	-0.086896	0.106667
Market Return	0.000058	0.001043	-0.002974	0.004434
Private information	0.002676	0.015272	-0.121806	0.249431

Table 2. Estimation of the 7-Way Event Structure on a Stock-By-Stock Basis

The table reports the results from estimating equation (1). In Panel A, we report the estimated regression coefficients. In Panel B, we report the impulse sensitivities (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 equation (1) converges. For the other sample stocks, we pool data into an eighty-sixth regression.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A: Mean Estimated Regression Coefficients																	
Cancel Buy	**1.773**	**1.045**	**1.560**	**1.016**	**1.005**	**0.876**	**39.28**	**-1.041**	**-0.200**	**0.99**	**45.308**	**1.36**	**82.925**	0.068	**.380**	2.085	**0.288**
Cancel Sell	**0.888**	**1.712**	**1.002**	**1.512**	**0.735**	**1.095**	**36.70**	-0.108	**-0.558**	**1.15**	**-25.53**	**1.54**	**-70.07**	-2.006	**.419**	0.406	**0.352**
Limit Buy	**1.506**	**1.101**	**1.354**	**0.924**	**0.951**	**0.865**	**136.46**	**0.574**	**-0.318**	**1.32**	2.442	**1.47**	**81.602**	**1.905**	**.404**	**7.154**	**0.346**
Limit Sell	**1.114**	**1.520**	**0.960**	**1.317**	**0.842**	**.0997**	**154.9**	**-0.362**	**0.399**	**1.41**	**18.010**	**1.49**	**-84.91**	0.837	**.443**	**-10.53**	**0.387**
Market Buy	**0.757**	**0.570**	**0.674**	**0.575**	**1.089**	**0.469**	**-132.8**	**0.835**	-0.018	**1.17**	**90.639**	**1.67**	**121.96**	1.074	**.768**	**9.068**	**0.286**
Market Sell	**0.504**	**0.855**	**0.612**	**0.732**	**0.647**	**1.074**	**-114.0**	**0.207**	**0.611**	**0.77**	**-104.8**	**1.14**	**-105.4**	-0.043	**.719**	**-12.90**	**0.170**
Panel B: Mean Impulse Sensitivities (%)																	
Cancel Buy	**2.41**	**0.812**	**2.21**	**0.83**	**0.80**	**0.45**	0.04	**-0.32**	**-0.16**	**0.14**	**0.57**	**0.51**	**0.47**	-0.07	**0.20**	0.01	**0.26**
Cancel Sell	**0.83**	**2.171**	**0.71**	**2.08**	**0.32**	**0.83**	0.06	-0.14	**-0.39**	**0.14**	**-0.57**	**0.52**	**-0.34**	**-0.16**	**0.42**	-0.12	**0.28**
Limit Buy	**2.72**	**1.023**	**3.93**	**1.18**	**1.31**	**0.80**	**3.17**	**0.69**	**-0.41**	**0.38**	**1.08**	**0.64**	**0.28**	**0.48**	**0.63**	**0.71**	**0.49**
Limit Sell	**0.99**	**2.559**	**1.02**	**3.40**	**0.73**	**1.18**	**3.50**	**-0.39**	**0.55**	**0.48**	**-1.13**	**1.04**	**-0.38**	**0.38**	**0.79**	**-0.75**	**0.66**
Market Buy	0.01	**-0.263**	**0.15**	-0.12	**1.58**	**0.12**	**-2.13**	**0.48**	0.01	**0.31**	**1.57**	**0.40**	**0.64**	0.068	**1.64**	**0.40**	0.02
Market Sell	**-0.23**	**0.166**	**-0.09**	**0.26**	**0.21**	**1.87**	**-1.98**	0.04	**0.34**	0.21	**-1.34**	**0.45**	**-0.35**	**-0.23**	**1.53**	**-0.60**	0.13
No Activity	**-6.74**	**-6.468**	**-7.95**	**-7.64**	**-4.98**	**-5.27**	**-2.67**	-0.36	0.06	**-1.70**	**-0.59**	**-3.60**	-0.10	-0.45	**-5.20**	0.36	**-1.86**
Panel C: Hypothesis Predicted Signs of the Impulse Sensitivities																	
Cancel Buy										+					+		
Cancel Sell										+					+		
Limit Buy	+		-				+	+		+	-	+	+	≠0	+	+	+
Limit Sell		+		-			+		+	+	+	+	-	≠0	+	-	+
Market Buy					-		-	+		+	-	-	+	≠0	+	+	
Market Sell						-	-		+	+	+	-	-	≠0	+	-	
No Activity										-					-		

Coefficients for bid size, ask size, time, and time squared are multiplied by 1,000. 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 impulse sensitivities 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 impulse sensitivities (in Panel B) have the same sign as the mean.

Table 3. Estimation of the 13-Way Event Structure on a Stock-By-Stock Basis

The table reports the results from estimating equation (1). In Panel A, we report the estimated regression coefficients. In Panel B, we report the impulse sensitivities (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 equation (1) converges. For the other sample stocks, we pool data into an eighty-sixth regression.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A. Regression Coefficient Estimates																	
Cancel Buy	**0.46**	**-4.69**	**2.44**	**-2.84**	**2.03**	**-4.06**	**48.51**	-0.43	**-0.43**	**0.96**	**12.13**	**1.40**	**36.44**	-0.19	**0.40**	-1.77	**0.22**
Cancel Sell	**-4.61**	0.33	**-2.98**	**2.46**	**-4.3**	**2.15**	**56.49**	**-0.48**	**-0.26**	**1.08**	5.23	**1.44**	**-35.66**	-0.54	**0.42**	-3.16	**0.28**
BTQ Limit Buy	**1.26**	**1.15**	**1.51**	**1.20**	**0.82**	**0.84**	7.21	**-1.55**	**0.60**	**0.86**	-3.68	**0.93**	1.15	0.08	**0.74**	8.12	0.08
ATQ Limit Buy	**1.16**	**1.07**	**1.23**	**0.91**	**0.80**	**0.73**	**159.0**	**-0.87**	-0.09	**1.31**	54.84	-1.81	**104.9**	3.65	**0.27**	4.66	**0.20**
ITQ Limit Buy	**1.28**	**0.87**	**1.35**	**0.92**	**0.79**	**0.87**	**237.2**	**2.37**	**-2.05**	**1.28**	6.21	**0.90**	**115.8**	2.67	**0.30**	9.34	**0.24**
ITQ Limit Sell	**1.03**	**1.08**	**0.93**	**1.33**	**0.83**	**1.04**	**275.8**	**-1.85**	**1.64**	**0.98**	**16.65**	**0.90**	**-126.8**	0.48	**0.28**	**-11.16**	**0.31**
ATQ Limit Sell	**0.71**	**1.32**	**0.74**	**1.40**	**0.71**	**1.06**	**179.7**	0.17	**-0.37**	**1.19**	**38.43**	**1.30**	**-93.21**	1.18	**0.32**	**-14.01**	**0.27**
BTQ Limit Sell	**1.30**	**1.04**	**0.93**	**1.36**	**0.67**	**0.98**	14.70	0.17	**-1.02**	**0.96**	-6.38	**1.44**	-4.20	4.04	**0.84**	**-7.69**	**0.29**
Mkt. Limit Buy	**1.03**	**0.77**	**0.94**	**0.80**	**0.94**	0.44	**-468.3**	**1.89**	**-1.00**	**1.34**	34.03	**1.84**	**174.7**	-0.09	**0.69**	9.28	**0.20**
Mkt. Limit Sell	0.51	**1.06**	0.44	**0.78**	**0.84**	**1.38**	**-379.5**	**-0.74**	**1.27**	**1.20**	-15.45	**1.66**	**-131.1**	**-3.00**	**0.68**	**-16.58**	-0.41
Market Buy	**0.78**	**0.57**	**0.92**	**0.81**	**1.36**	**0.64**	2.69	-0.35	0.29	**1.01**	**65.28**	**1.16**	**123.8**	2.78	**0.79**	5.10	-0.15
Market Sell	**0.59**	**0.81**	**0.81**	**.093**	**0.61**	**1.40**	-9.69	-0.46	0.32	-.49	**-76.94**	0.67	**-146.3**	1.47	**0.72**	-4.57	0.07
Panel B. Mean Impulse Sensitivities (%)																	
Cancel Buy	0.04	**-1.05**	**1.74**	**-1.15**	**1.06**	**-1.10**	0.08	**-0.04**	**-0.07**	**0.03**	0.01	**0.14**	**0.06**	-0.04	**0.08**	0.01	**0.08**
Cancel Sell	**-0.93**	0.05	**-1.09**	**1.61**	**-1.02**	**1.05**	0.02	**-0.04**	**-0.05**	**0.04**	0.01	**0.14**	**-0.06**	**-0.04**	**0.10**	-0.04	**0.93**
BTQ Limit Buy	**1.17**	**1.07**	**1.45**	**0.92**	**0.51**	**0.50**	**-0.36**	**-0.37**	**0.29**	**0.12**	**-0.15**	**0.34**	-0.00	-0.14	**0.85**	0.06	**0.18**
ATQ Limit Buy	**1.09**	**0.02**	**1.80**	**0.44**	**0.65**	**0.41**	**1.07**	**-0.34**	-0.14	**0.10**	-0.12	**0.23**	**0.54**	**0.42**	-0.06	0.27	**0.14**
ITQ Limit Buy	**1.21**	**0.78**	**1.74**	**0.62**	**0.73**	**0.50**	**2.26**	**1.04**	**-1.07**	**0.22**	0.10	0.17	**0.80**	**0.32**	0.37	**0.57**	**0.29**
ITQ Limit Sell	**0.70**	**1.15**	**0.54**	**1.56**	**0.44**	**0.74**	**2.55**	**-0.78**	**0.96**	**0.20**	**0.14**	0.12	**-0.80**	0.19	-0.08	**-0.37**	**0.43**
ATQ Limit Sell	**0.55**	**0.98**	**0.40**	**1.53**	**0.44**	**0.55**	**1.17**	-0.07	-0.23	**0.16**	**0.28**	**0.31**	**-0.45**	0.25	0.01	**-0.43**	**0.22**
BTQ Limit Sell	**1.00**	**1.03**	**0.86**	**1.20**	**0.86**	**0.45**	-0.10	**0.14**	**-0.37**	**0.25**	0.07	**035**	0.00	-0.02	**1.01**	-0.12	0.08
Mkt. Limit Buy	**0.32**	**0.12**	**0.28**	**1.69**	**0.69**	**0.18**	**-1.64**	**0.27**	**-0.12**	**0.16**	0.16	**0.36**	**0.60**	**-0.11**	**0.57**	**0.24**	0.05
Mkt. Limit Sell	**0.22**	**0.39**	**0.19**	**0.34**	**0.23**	**0.78**	**-1.50**	-0.02	**0.23**	**0.19**	0.01	**0.39**	**-0.42**	**-0.28**	**0.56**	**-0.31**	-0.10
Market Buy	**0.59**	**0.23**	**0.60**	**0.39**	**1.60**	**0.46**	**-0.54**	**0.20**	**0.11**	**0.19**	**0.57**	**0.25**	**0.90**	**0.18**	**1.26**	**0.17**	-0.02
Market Sell	**0.25**	**0.67**	**0.42**	**0.69**	**0.50**	**1.90**	**-0.65**	**0.09**	**0.19**	**0.07**	**-0.37**	**0.35**	**-0.99**	0.03	**1.12**	**-0.29**	**0.14**
No Activity	**-6.24**	**-6.08**	**-8.97**	**-8.97**	**-6.20**	**-6.47**	**-2.36**	-0.06	0.28	**-1.70**	**-0.72**	**-3.20**	**-0.17**	**0.74**	**-5.48**	0.22	**-1.60**

BTQ = Behind-The-Quote; ATQ = At-The-Quote; ITQ = Inside-The-Quote. Coefficients for bid size, ask size, time, & time squared are multiplied by 1,000. Coefficients for relative volume & own return squared are multiplied by 1,000,000 & 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 impulse sensitivities 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 impulse sensitivities (in Panel B) are in the same direction as the mean.

Table 4. OLS Regressions of Orders / No Activity Events Aggregated Over Five Minute Intervals

The table reports the results from estimating equation (1) aggregated over five minute intervals. In Panel A, we report the estimated OLS regression coefficients, where each row is one OLS regression. In each row, the dependent variable is the change in number of orders or no activity events for a given stock over a five minute interval compared to the previous five minute interval. In Panel B, we report the economic sensitivities (change in the number of orders or no activity events caused by a one standard deviation shock in the explanatory variable).

OLS Dependent Variable	Last 5 Min Can. Buy	Last 5 Min Can. Sell	Last 5 Min Limit Buy	Last 5 Min Limit Sell	Last 5 Min Mkt. Buy	Last 5 Min Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A: Estimated OLS Regression Coefficients																	
Cancel Buy	**-0.41**	**0.23**	**0.06**	**-0.10**	**0.11**	**-0.03**	7.37	0.001	-0.006	-0.07	72	-147	**1170**	**-60**	0.37	**88.97**	-1.41
Cancel Sell	**0.19**	**-0.37**	**-0.05**	0.01	**0.03**	**0.04**	2.28	0.001	-0.008	-0.05	**-227**	61	**-1986**	**-52**	0.63	29.38	-0.62
Limit Buy	**0.16**	**0.41**	**-0.43**	**-0.17**	**0.14**	**0.04**	-0.38	0.003	-0.021	-0.18	**-613**	**748**	**1292**	**-72**	0.09	**147.67**	-0.44
Limit Sell	**0.29**	**0.25**	-0.01	**-0.53**	**0.09**	**0.05**	0.70	0.003	-0.025	-0.12	137	-324	-841	**-55**	0.10	43.60	2.54
Market Buy	0.05	**0.45**	0.02	**-0.15**	**-0.30**	**0.06**	-17.50	0.003	-0.019	-0.19	**-722**	**755**	**2975**	**-41**	0.06	**199.90**	-3.46
Market Sell	**0.37**	**0.13**	**-0.13**	-0.01	**0.06**	**-0.39**	-19.56	0.004	-0.036	-0.19	-245	107	**-1658**	**-49**	0.82	31.22	-2.58
No Activity	**0.62**	**0.67**	**-0.21**	**-0.34**	**-0.11**	0.04	-24.16	0.005	-0.040	-0.13	-133	111	**-3214**	**-297**	-1.69	**186.78**	**-5.56**
Panel B: Economic Sensitivities (Change in the Number of Orders or No Activity Events Caused By One Std Dev Shock in the Explanatory Variable)																	
Cancel Buy	**-20.03**	**11.00**	**5.10**	**-8.34**	**8.88**	**-1.92**	0.09	0.13	-0.10	-0.04	0.18	-0.23	**0.57**	**-1.37**	0.17	**0.58**	-0.25
Cancel Sell	**9.21**	-17.60	**-4.11**	0.78	**2.27**	**2.76**	0.03	0.15	-0.15	-0.03	**-0.57**	0.10	**-0.98**	**-1.18**	0.29	0.19	-0.11
Limit Buy	**7.81**	**19.19**	-37.19	**-13.76**	**10.71**	**3.24**	0.00	0.42	-0.38	-0.10	**-1.53**	**1.19**	**0.63**	**-1.64**	0.04	**0.96**	-0.08
Limit Sell	**14.28**	**11.67**	-0.53	**-44.08**	**6.77**	**4.21**	0.01	0.45	-0.46	-0.06	0.34	-0.51	-0.41	**-1.24**	0.04	0.28	0.45
Market Buy	2.31	**21.01**	1.56	**-12.20**	-23.92	**4.44**	-0.22	0.42	-0.34	-0.11	**-1.80**	**1.20**	**1.46**	**-0.94**	0.03	**1.29**	-0.61
Market Sell	**18.35**	**6.20**	**-11.01**	-1.07	**4.75**	**-30.05**	-0.25	0.63	-0.66	-0.10	-0.61	0.17	**-0.81**	**-1.11**	0.38	0.20	-0.46
No Activity	**30.16**	**31.55**	**-17.86**	**-28.20**	**-8.59**	3.11	-0.31	0.77	-0.73	-0.07	-0.33	0.18	**-1.58**	**-6.72**	-0.77	**1.21**	**-0.98**

Coefficients for bid size, ask size, time, and time squared are multiplied by 1,000. Coefficients for relative volume (own return squared) are multiplied by 1,000,000 (10,000).
Bold numbers are significant at the .01 level based on a standard t-test. The sample size is 11,398.

Table 5. Separating Automatically Executed Orders and Floor Orders

We report impulse sensitivities (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 equation (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 impulse responses are statistically significant at traditional levels. Panel B compares the magnitudes of the impulse responses for the floor and automatic marketable orders. The reported number is the absolute value of the ratio of the floor-execution sensitivity divided by the automatic-execution sensitivity.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A. Impulse Sensitivities (%)																	
Cancel Buy	2.59	1.03	1.90	0.85	0.73	0.38	0.62	0.10	-0.14	0.06	0.47	-0.41	0.55	-0.19	0.31	0.07	0.24
Cancel Sell	1.02	2.36	0.82	1.76	0.40	0.80	0.89	0.10	-0.75	0.07	-0.14	0.14	-0.56	-0.26	0.47	-0.08	0.25
Limit Buy	1.92	0.89	3.12	1.19	1.17	0.56	3.40	-0.43	-0.08	0.31	-0.36	0.24	0.55	0.12	0.84	0.28	0.72
Limit Sell	0.89	1.82	1.16	2.94	0.57	1.17	3.37	-0.48	-0.30	0.29	0.95	-0.72	-0.55	0.17	1.01	-0.42	0.82
Floor MB	1.63	-0.09	0.51	0.12	2.10	0.41	-3.21	-0.14	-0.40	0.69	-0.14	0.14	1.52	-0.02	1.95	0.32	0.43
Floor MS	-0.11	0.26	0.10	0.61	0.45	2.62	-3.12	0.21	-0.53	0.58	-0.14	0.17	-1.37	0.30	1.84	-0.50	0.40
Auto-ex MB	0.01	0.001	0.01	-0.001	0.03	-0.0001	-0.12	0.01	-0.01	0.01	-0.02	-0.02	0.02	-0.01	0.01	0.01	-0.001
Auto-ex MS	-0.0008	0.01	0.0006	.0008	-0.00	0.01	-0.06	-0.01	0.002	0.01	-0.001	0.003	-0.01	-0.004	0.005	0.0002	-0.002
No Activity	-6.50	-6.29	-1.76	-7.51	-5.77	-5.97	-1.76	0.64	2.23	-2.05	-0.59	0.45	-0.14	0.50	-6.45	0.31	-2.89
Panel B. Absolute Value of Floor / Automatic																	
Floor/Elec MB	163	90	51	120	70	4,100	26	14	40	69	7	7	76	20	195	32	430
Floor/Elec MS	137	26	166	762	--	262	52	21	265	58	140	56	137	75	368	2,500	200

Table 6. Impulse Sensitivities (%) of the 7-Way Event Structure By Order Size

The table reports the impulse sensitivities (change in the probability of an event caused by a one standard deviation shock in the explanatory variable). To do this, we first estimate equation (1) and evaluate the estimated logistic equation at the mean value of all explanatory variables. We then re-evaluate the estimated logistic after adding a one standard deviation to one explanatory variable and report the change in the probability.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A: Large Orders (> 9,999 shares)																	
Cancel Buy	0.04	0.02	0.04	0.03	0.02	0.02	0.01	0.002	-0.002	0.0009	0.03	-0.02	0.004	-0.003	0.06	-0.003	0.01
Cancel Sell	0.03	0.04	0.03	0.04	0.02	0.03	0.01	-0.09	0.002	0.007	-0.002	0.003	-0.01	-0.003	0.08	-0.004	0.01
Limit Buy	0.08	0.06	0.15	0.11	0.08	0.08	0.05	-0.07	0.004	0.02	-0.006	0.004	0.01	0.004	0.21	-0.008	0.04
Limit Sell	0.07	0.09	0.12	0.18	0.10	0.12	0.06	-0.36	-0.0001	0.03	-0.009	0.01	-0.01	0.02	0.28	-0.02	0.07
Market Buy	0.05	0.05	0.11	0.11	0.15	0.11	0.01	-0.11	0.003	0.02	0.21	-0.13	0.02	-0.02	0.24	0.02	0.02
Market Sell	0.04	0.05	0.08	0.09	0.09	0.14	0.03	-0.24	-0.02	0.03	-0.01	0.01	-0.04	-0.01	0.23	-0.03	0.02
No Activity	-0.33	-0.35	-0.55	-0.57	-0.49	-0.52	-0.18	0.89	0.02	-0.10	-0.21	0.13	0.02	0.01	-1.13	0.05	-0.18
Panel B: Medium Orders (999 < shares < 10,000)																	
Cancel Buy	1.10	0.57	0.94	0.55	0.48	0.36	0.75	-0.21	-0.27	0.23	0.13	-0.14	0.07	-0.10	0.57	0.03	0.22
Cancel Sell	0.64	1.17	0.62	1.02	0.41	0.58	0.82	-2.39	-0.04	0.22	-0.04	0.05	0.16	-0.08	0.67	-0.02	0.21
Limit Buy	1.30	0.85	1.88	1.19	0.98	0.82	0.18	-1.45	-0.79	0.61	-0.13	0.07	-0.19	0.13	1.54	0.06	0.73
Limit Sell	0.89	1.41	1.28	2.08	0.86	1.14	0.19	-1.19	-0.78	0.67	0.71	-0.54	0.09	0.18	1.62	-0.19	0.77
Mkt. Buy	0.52	0.35	0.80	0.57	1.61	0.62	-1.33	-0.93	-0.51	0.57	-0.03	0.04	-0.10	-0.19	1.61	0.15	0.44
Mkt. Sell	0.37	0.56	0.59	0.83	0.64	1.69	-1.31	-3.91	-0.23	0.55	0.05	0.07	0.81	-0.26	1.64	-0.28	0.44
No Activity	-4.85	-4.94	-6.14	-6.26	-5.00	-5.23	-2.65	10.11	2.59	-2.87	-0.57	0.42	-0.65	0.32	-7.67	0.24	-2.84
Panel C: Small Orders (< 1,000 shares)																	
Cancel Buy	2.53	1.10	1.97	1.01	0.81	0.50	0.02	0.15	-0.13	0.05	0.54	-0.45	0.51	-0.17	0.37	0.04	0.31
Cancel Sell	1.03	2.18	0.91	1.72	0.46	0.82	0.37	0.53	-1.44	0.09	-0.13	0.11	-0.48	-0.25	0.46	-0.08	0.30
Limit Buy	1.96	1.08	3.16	1.37	1.29	0.70	2.01	-1.31	0.47	1.84	-0.29	0.20	0.60	-0.03	0.71	0.26	0.64
Limit Sell	1.06	1.74	1.27	2.77	0.64	1.17	1.91	-1.87	-0.06	0.004	0.89	-0.70	-0.60	-0.02	0.76	-0.36	0.70
Mkt. Buy	0.35	0.11	0.65	0.30	2.22	0.51	-2.62	-0.48	-0.48	0.49	-0.16	0.14	1.23	0.07	1.80	0.25	0.38
Mkt. Sell	0.07	0.42	0.27	0.74	0.52	2.40	-2.34	0.47	0.63	0.40	-0.11	0.13	-1.15	-0.17	1.63	-0.39	0.32
No Activity	-7.03	-6.65	-8.26	-7.93	-5.95	-6.12	6.47	2.50	2.72	-1.24	-0.73	0.56	-0.11	0.56	-5.58	0.29	-2.68

.

Table 7. Impulse Sensitivities (%) of the 7-Way Event Structure By Volume and Price Category

The table reports the impulse sensitivities (change in the probability of an event caused by a one standard deviation shock in the explanatory variable) derived from equation (1) estimates.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A: Highest Volume Stocks																	
Cancel Buy	2.45	0.95	1.76	0.81	0.69	0.37	0.16	-0.28	-0.08	0.16	0.45	0.27	0.24	-0.19	0.27	0.10	0.26
Cancel Sell	0.94	2.25	0.79	1.62	0.39	0.75	0.26	-0.17	-0.24	0.13	-0.49	0.37	-0.18	-0.16	0.38	-0.12	0.26
Limit Buy	1.74	0.73	2.66	0.92	0.93	0.42	3.53	0.28	-0.15	0.41	0.83	0.29	-0.62	0.22	0.66	0.51	0.48
Limit Sell	0.68	1.56	0.85	2.40	0.42	0.93	3.61	-0.23	0.21	0.46	-0.74	0.42	0.72	0.39	0.62	-0.58	0.44
Mkt. Buy	0.07	-0.17	0.37	0.006	2.10	0.12	-2.24	0.47	-	0.41	1.82	0.55	0.06	-0.02	1.91	0.36	0.02
Mkt. Sell	-0.20	0.15	-0.006	0.45	0.17	2.45	-2.17	0.03	0.44	0.27	-1.67	0.54	-0.03	-0.30	1.79	-0.65	0.09
No Activity	-5.69	-5.48	-6.45	-6.24	-4.76	-5.06	-3.15	-0.25	-0.13	-1.86	-0.18	-2.46	-0.19	-0.06	-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	0.02	-0.34	-0.21	0.15	0.77	0.49	0.70	0.06	0.07	-0.07	0.25
Cancel Sell	0.71	2.36	0.65	2.47	0.21	0.88	-0.07	-0.20	-0.38	0.09	-0.63	0.41	-0.68	-0.10	0.49	-0.01	0.47
Limit Buy	3.12	1.39	6.07	1.32	1.76	1.13	2.28	1.12	-0.64	0.25	1.21	0.72	-0.14	1.12	0.87	1.06	0.79
Limit Sell	1.36	2.98	1.02	4.72	1.07	1.36	2.93	-0.43	0.96	0.40	-1.53	1.00	0.09	0.62	1.02	-0.77	1.20
Mkt. Buy	0.05	-0.29	-0.08	-0.21	0.94	0.17	-1.82	0.58	0.01	0.17	0.87	0.39	1.12	0.10	1.17	0.44	0.06
Mkt. Sell	-0.24	0.16	-0.22	0.07	0.20	0.99	-1.69	0.06	0.43	0.12	0.84	0.38	-0.51	-0.23	1.20	-0.46	0.11
No Activity	-7.72	-7.24	-10.90	-9.31	-5.15	-5.08	-1.64	-0.78	-0.17	-1.20	-0.58	-3.41	0.41	-1.58	-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	-0.24	-0.46	-0.24	0.06	0.70	0.64	0.79	0.13	0.14	-0.20	0.21
Cancel Sell	0.73	1.60	0.56	2.80	0.28	0.93	-0.33	-0.43	-0.33	0.26	-0.68	0.87	-0.35	-0.22	0.41	-0.28	0.07
Limit Buy	4.85	1.27	4.41	1.71	1.60	1.32	3.52	1.35	3.52	0.51	1.78	1.14	0.39	0.36	0.25	0.73	0.22
Limit Sell	1.35	4.69	1.49	4.23	1.00	1.52	4.13	-0.83	4.13	0.69	-1.71	0.77	-0.07	0.03	0.96	-1.16	0.48
Mkt. Buy	-0.27	-0.44	-0.11	-0.33	0.97	0.04	-2.22	0.43	-2.22	0.22	0.85	0.42	1.73	0.27	1.47	0.37	0.003
Mkt. Sell	-0.31	.017	-0.17	-0.02	0.24	1.34	-1.83	0.06	-1.83	0.17	-0.77	0.79	-1.09	-0.07	1.22	-0.60	0.26
No Activity	-8.15	-7.09	-8.87	-9.13	-4.99	-5.78	-3.00	-0.12	3.00	-1.94	-1.40	-4.65	-0.17	-0.50	-4.48	1.15	-1.06
Panel D: Low-Volume Stocks																	
Cancel Buy	3.59	.98	4.11	.86	1.50	.43	-.39	.05	.003	.004	.043	9.73	.71	-.60	.25	.68	1.21
Cancel Sell	.57	2.86	.87	3.76	.27	1.65	.13	-.08	-.07	.03	-1.54	3.90	-.31	-.65	.46	-.18	.67
Limit Buy	6.07	2.34	8.79	1.55	3.73	2.70	.17	-.08	-.22	.07	-1.23	7.95	1.58	.004	.39	2.33	1.42
Limit Sell	1.81	5.91	1.62	7.56	3.07	3.48	.56	-1.06	.15	.07	-1.28	34.84	-1.75	-.25	1.02	-1.49	1.99
Mkt. Buy	.01	-.57	-.49	-.62	1.32	.33	-1.75	.16	-.06	-.001	16.46	-6.78	.21	.42	1.36	1.56	.52
Mkt. Sell	-.17	.28	.11	.22	1.28	2.56	-1.50	.16	.01	-.01	-5.51	-7.23	-.06	.31	1.21	-1.14	.14
No Activity	-11.90	-11.83	-45.40	-13.35	-11.19	-11.17	2.77	.85	.19	-.17	-6.92	-42.42	-.38	.77	-4.71	-1.75	-5.51

Table 8. Impulse Sensitivities (%) for the Robustness Checks of the 7-Way Event Structure

We report impulse sensitivities (change in an event's probability due to a shock in an explanatory variable). To do this, we estimate equation (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.

Event	Last Can. Buy	Last Can. Sell	Last Limit Buy	Last Limit Sell	Last Mkt. Buy	Last Mkt. Sell	Percent Spread	Rel. Bid Size	Rel. Ask Size	Rel. Vol.	Own Ret.	Own Ret. Sqr.	Mkt. Ret.	Time	Time Sqr.	Private Infor-mation	NYSE Not At NBBO
Panel A. Correcting for Possible Order Splitting																	
Cancel Buy	1.48	0.99	1.72	0.87	0.69	0.44	0.61	0.40	-0.25	0.07	0.55	-0.47	0.49	-0.16	0.34	0.08	0.26
Cancel Sell	0.92	1.40	0.83	1.60	0.42	0.75	0.67	0.39	-0.69	0.10	-0.14	0.13	-0.50	-0.21	0.49	-0.07	0.27
Limit Buy	1.84	1.06	2.00	1.39	1.23	0.67	2.39	-0.76	-0.79	0.27	-0.36	0.22	0.50	0.14	0.92	0.28	0.81
Limit Sell	1.09	1.78	1.42	2.00	0.68	1.26	3.31	-3.41	-0.34	0.30	0.97	-0.74	-0.51	0.18	1.04	-0.44	0.84
Market Buy	0.41	0.10	0.78	0.35	2.07	0.53	-3.60	0.01	-0.42	0.78	-0.18	0.17	1.59	-0.06	2.03	0.36	0.42
Market Sell	0.10	0.47	0.35	0.86	0.55	2.28	-3.41	0.67	-0.55	0.66	-0.15	0.18	-1.42	-0.35	1.94	-0.52	0.39
No Activity	-5.86	-5.80	-7.13	-7.08	-5.69	-5.92	-0.88	2.69	3.06	-2.21	-0.67	0.49	-0.15	0.46	-6.79	0.30	-3.02
Panel B. Orders in the Final 15 Minutes of Trading																	
Cancel Buy	2.09	0.68	1.39	0.51	0.46	0.30	1.48	-5.51	0.01	-0.20	-0.001	-0.27	0.70	-6.46	-6.49	-0.09	0.29
Cancel Sell	0.76	1.88	0.47	1.38	0.21	0.67	2.53	0.98	-0.58	-0.07	-0.08	0.20	-0.38	-5.87	-6.51	-0.30	0.67
Limit Buy	1.65	0.68	2.96	1.36	1.02	0.56	9.90	-3.21	0.76	-0.14	-0.26	0.14	0.56	-16.02	-13.58	-0.16	0.34
Limit Sell	0.87	2.08	1.54	3.24	0.83	1.00	9.34	2.58	-0.50	0.35	0.05	-0.08	-0.36	-16.09	-15.39	-0.84	0.46
Market Buy	0.02	-3.96	0.34	-0.04	3.18	0.55	-8.38	-2.06	-1.12	0.95	-0.46	0.53	1.37	-14.80	82.02	1.95	0.03
Market Sell	-0.41	-0.07	-0.11	0.19	0.36	2.26	-5.13	-0.75	0.52	0.23	-0.25	0.41	-1.18	-12.47	-12.44	-1.93	-0.02
No Activity	-5.00	-4.86	-6.61	-6.66	-6.08	-5.36	-9.76	7.96	1.97	-1.12	1.02	-0.94	-0.71	71.74	-27.59	1.41	-1.18

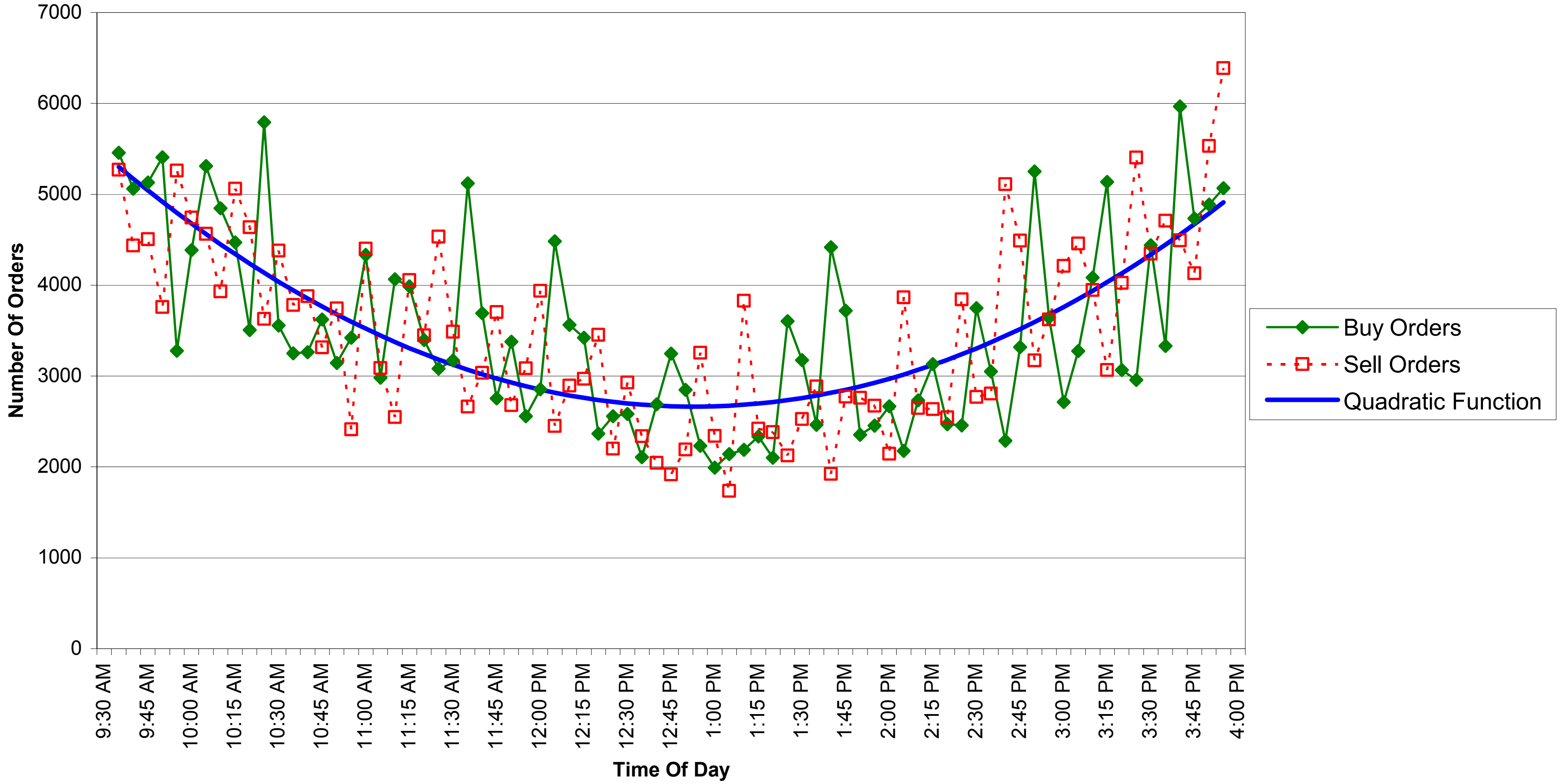

Figure 1. Aggregate Buy and Sell Orders By Time Of Day.

Total number of buy orders and sell orders for 148 stocks by time of day on April 3, 2001.