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Anatomy of the trading process Empirical evidence on the behavior of institutional traders

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Abstract

This paper examines the behavior of institutional traders. We use unique data on the equity transactions of 21 institutions of differing investment styles which provide a detailed account of the anatomy of the trading process. The data include information on the number of days needed to fill an order and types of order placement strategies employed. We analyze the motivations for trade, the determinants of trade duration, and the choice of order type. The analysis provides some support for the predictions made by theoretical models, but suggests that these models fail to capture important dimensions of trading behavior.

Key words: Institutional investors; Microstructure; Trading strategies
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1. Introduction

Interest in the behavior of institutional investors has increased greatly in recent years, motivated in part by the rapid growth and sheer magnitude of institutional trading both in the U.S. and in other industrialized nations. Schwartz and Shapiro (1992) report that in 1990 U.S. institutions accounted for 72% of share volume on the New York Stock Exchange (NYSE). They also report that institutions accounted for 73% of the value of trading on the London Stock Exchange and 77% of share volume on the Tokyo Stock Exchange. Several recent studies (Chan and Lakonishok, 1993a, b; Lakonishok, Shleifer, and Vishny, 1992; Keim and Madhavan, 1994) examine the price movements associated with institutional trades. Yet relatively little is known about the actual trading behavior of institutional investors. To fill some of the gaps in our understanding of their behavior, this paper analyzes empirically the equity transactions of institutional traders.

Institutional trading behavior is important for several reasons. An institution that wishes to make a large change in its equity position may trade over several days, and its continued presence on one side of the market could significantly affect asset price dynamics. In particular, an institution that pursues a technical trading strategy, e.g., a contrarian or momentum strategy, could tend to stabilize or exacerbate price movements.[1] Institutions' choice of order type might also affect market liquidity and execution costs. To the extent that institutions rely on 'active' trading strategies based on market orders, they act as demanders of liquidity. By contrast, if they rely on 'passive' trading strategies using limit orders, institutions can be viewed as liquidity providers. Finally, and perhaps most importantly, there is an extensive theoretical literature whose predictions regarding the rational trading behavior of an institution remain largely untested. Since institutional traders expend considerable time and effort developing order placement strategies, the actual trading behavior of this investor group provides an important benchmark against which to gauge the validity of extant theoretical models of the trading process.

We use data on the equity trades (which have a total market value of over $83 billion) of 21 institutions during the period 1991 to 1993. The data are unique in several respects, and permit tests of detailed hypotheses regarding the trade execution process, including the interaction between the size of trade, investment style of the institution, and the way in which orders are presented to the market.

We first analyze whether buyer- or seller-initiated trades are motivated by past price movements. There is considerable heterogeneity in investment style across

[1] We investigate below whether an institution's trading behavior is consistent with trading patterns implied by contrarian or momentum strategies. We do not, however, investigate the 'herding behavior' suggested by some models (e.g., DeLong, Shleifer, Summers, and Waldman, 1990; Scharfstein and Stein, 1990; Froot, Scharfstein, and Stein, 1992) where institutional trading is cross-sectionally correlated. Such herding may arise because traders respond in a similar way to correlated information signals, or because agency considerations create inducements for managers to mimic one another. If so, such behavior serves to amplify the effects of institutional trading on stock prices.

institutions. For some of the institutions in our sample, the buy–sell decision has no association with prior excess returns. For other institutions, there is a significant relation between trades and past excess returns. However, the overall effect of these strategies may be offsetting, because some traders pursue contrarian strategies while others follow trends. Surprisingly, the motivation for the trade decision is often not symmetric for buys versus sells. For example, some institutions that buy stocks after they decline in price do not follow the same trading rule when they sell.

We then examine the process by which the desired demands are translated into executed trades. Larger desired quantities are spread over a longer time period and are associated with longer trading durations. This is consistent with theoretical models such as Kyle (1985). However, buys take longer to execute than equivalent-sized sells, suggesting that traders perceive that price impacts of buys are greater than sells. This result augments previous empirical research that finds an asymmetric price response for buyer- versus seller-initiated trades (e.g., Kraus and Stoll, 1972; Madhavan and Smidt, 1991; Keim and Madhavan, 1994). Surprisingly, the duration of trading increases with market capitalization, holding constant order size. Our analysis of order type suggests a high demand for immediacy, which is consistent with short average duration of trade and the fact that most orders are completely filled. Further, the choice of order type is strongly linked to the trading style of the institution. Although our findings are consistent with the major implications of theoretical trading models regarding order fragmentation, they also suggest that those models fail to incorporate important dimensions of trader behavior. In particular, in most models of trading (see, e.g., Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1987, among others) the motivation for, and execution of, orders is symmetric.

The paper is organized as follows: Section 2 describes the hypotheses associated with the trading process that we analyze empirically; Section 3 describes the data; Section 4 presents an empirical analysis of the trading process; and Section 5 summarizes the main findings.

2. Empirical hypotheses

We begin by describing the main predictions on trader behavior suggested by theoretical models of trading. These hypotheses are the subject of our empirical tests.

2.1. The motivation for trade

Institutional trades result from institutions' desires to adjust their portfolio positions. In most theoretical models, trading arises because of new information signals. However, there are many other factors that may trigger a position adjustment. For example, trades may be induced by lumpy infusions (withdrawals) of cash, along with an institution's reluctance to hold large cash balances. These exogenous cash flows (and thus, institutional trades) are potentially related to past returns. Other traders use technical trading strategies that use past price movements to forecast future returns. For example, if institutional traders follow so-called 'positive feedback' strategies by buying in up markets and selling in down markets, we expect buy (sell) orders to follow positive (negative) prior returns. Alternatively, some institutions might follow contrarian ('negative feedback') strategies, implying the opposite relation. The extent to which institutional trades depend on past performance is important, since positive feedback strategies exacerbate short-run price volatility, while negative feedback strategies have the opposite effect. Alternatively, as institutions pursue a variety of different investment styles, their aggregate actions may prove offsetting. The overall impact of these effects on volatility is an empirical question that we do not examine here. A necessary condition for any effect to exist, however, is that some feedback strategy be employed.

Position adjustments may also be driven by agency problems, e.g., 'window dressing', where a fund manager seeks to buy winners and sell losers before accounting statements are made public. Further, for some institutions, trades are determined primarily by pre-determined investment objectives. For example, index traders seek to mimic the returns on a particular financial index, and their trades are largely determined by movements in the index.

2.2. Trade duration and order breakup

In most dynamic trading models (e.g., Kyle, 1985; Foster and Vishwanathan, 1990; Madhavan and Smidt, 1993) optimizing traders employ a decision rule to specify their order quantity in each period as a function of then-prevailing price quotations. Thus, trading takes place until the asset's price converges to the trader's reservation price. The greater the deviation between the asset and reservation prices (based either on information or on liquidity considerations, as described above), the greater the desired order size and the longer the interval over which trading occurs. Intuitively, a rational trader reduces the overall price impact of a large order by breaking it up into several smaller trades.[2]

In many models, price impacts are inversely related to market liquidity either because market makers' inventory control costs decrease with trading frequency, or because asymmetric information costs are less severe for widely-followed stocks.[3] This suggests that the benefits of trading over a longer horizon are greatest in thin markets, so that correcting for order size, trade duration should decrease with market liquidity.

[2] See Barclay and Warner (1993), who examine empirically the relation between trade size and price movements.

[3] See, e.g., Madhavan and Smidt (1993) who develop and test a model with both inventory and information effects.

2.3. The choice of order type

An important decision for the trader concerns how to present the order to the market. However, there are relatively few theoretical models where order type is a decision variable.[4] Theoretical models where traders make strategic decisions about order type suggest a trade-off between active and passive trading strategies. Active trading strategies that use market orders provide, immediate execution, but at the cost of potentially large price impacts. Passive trades (e.g., using limit orders or crossing networks) offer an opportunity for price improvement, but impose opportunity costs because trade execution is not assured. A passive trading strategy may also incur adverse selection costs because it offers an option to informed traders.

We hypothesize that active managers who trade on information that is short-lived (e.g., technical traders whose decisions are based on momentum) prefer to use market orders to assure rapid execution. Similarly, indexers, whose objective is to mimic the behavior of some well-defined benchmark, should use market orders to maximize their correlation with the benchmark index, which is normally valued with closing prices. On the other hand, value managers trading on longer-term information do not always require quick execution. They might prefer to trade more discreetly, using working or limit orders. Passive trading strategies might also be adopted by managers with large orders, for whom the price impact associated with market orders would far outweigh the opportunity costs associated with nonexecution. This argument would suggest that the benefits of a passive trading strategy are greatest in thin markets where liquidity is low and price impacts are large.

3. Data sources

The data used in this paper were collected by the Plexus Group, in conjunction with their advisory service for institutional investors. The data contain complete information on 62,000 equity orders (each of which may result in multiple transactions), with a total value of over $83 billion, placed by 21 institutions for various subperiods from January 1991 to March 1993. The institutions include investment managers, index funds, and pension funds, and differ in their motivations for trade, their trading styles, and the stocks traded. Although the institutions are identified only by number (to ensure confidentiality), the Plexus Group provided us with a general description of each institution's investment style. Three broad categories of investment style are represented in our sample: value-based investing, where the institution follows a strategy based on the analysis of fundamental factors;

[4] In many models, e.g., Kyle (1985), Glosten and Milgrom (1985), and Easley and O'Hara (1987), investors are restricted to using market orders; Rock (1990), Easley and O'Hara (1991), Angel (1991), and Kumar and Seppi (1993) present models of limit orders; Handa and Schwartz (1991) and Harris and Hasbrouck (1992) examine empirically the differences in the price effects of limit and market orders.

technical or momentum strategies, where the strategy is based on market momentum and also possibly on fundamental factors; and index strategies, where the institution's objective is to mimic the returns of a particular stock index.

For each institution, the data contain (among other items) the following information:

(1) the institution or manager initiating the trade,
(2) the cusip number of the stock to be traded,
(3) the date when the trading decision was made,
(4) the desired number of shares in the order at the time of the trading decision, with a buy–sell indicator,
(5) the closing price on the day before the decision to trade,
(6) the dates and number of desired shares corresponding to releases from the institution's trade desk to the brokers who fill the trade,
(7) the volume-weighted average trade price, number of shares traded, and date associated with the transaction(s) executed by the broker within a specific release,
(8) an indication of order-type, i.e., whether the trade was made using a market order, limit order, working order, or was executed using a crossing network.

These data differ from those used in other studies. First, unlike virtually all other transaction-level data, the data include the trading activity generated by a particular indicated desire to trade. This information is crucial to an analysis of trading behavior, because an order for a certain number of shares often results in several trades that span many different, and not necessarily adjacent, days. In most transaction-level data, the separate order partitions precipitated by a single order cannot be uniquely identified.

Second, the data identify the trade as buyer-initiated or seller-initiated. In most available databases, volumes are not signed and the trade initiation must be inferred indirectly by using time-stamped quotation data. Recent exceptions include Keim and Madhavan (1994) and Chan and Lakonishok (1993a). The data used by Chan and Lakonishok indicate whether an institutional trade was a buy or sell, but the information in their data does not identify whether that institution was the *initiator* of the trade. Hence, a purchase of a large block of stock by an institution that was initiated by an (external) seller would be recorded in their data as a buy. Initiation may be difficult to determine if an institution trades passively but opportunistically, or is known to follow a particular investment style that induces a latent demand for certain stocks. See, for example, Keim and Madhavan (1994).

Third, the data identify the type of order associated with the trade. Finally, the data cover a large number of transactions in a wide variety of stocks (including stocks listed on the NYSE, AMEX, and NASDAQ-NMS) made by institutions with very different trading styles.

Before performing any empirical analyses, we applied various filters to verify the accuracy of the data. In addition, we eliminated orders or transactions containing less than 100 shares, orders for stocks trading under $1.00, and orders that took longer than 21 calendar days to execute. The last filter was imposed because we feel that these transactions reflect either errors or sustained trading associated with acquiring a significant portion of the outstanding shares of a security.

The trade data described above were merged with prices and returns from files provided by the Center for Research in Security Prices (CRSP). Specifically, for the stock associated with each order, we obtained the closing transaction price for the day after the last transaction in the order. We also obtained market-adjusted returns over several multiweek intervals before the trade so that we could examine the underlying motivations for the trades. We adjusted the total returns for market movements by subtracting the CRSP value-weighted NYSE-AMEX index return for each day before a trade of a listed stock. The CRSP NASDAQ index return is used to adjust the pre-trade returns of NASDAQ-NMS stocks. We also used the CRSP data to verify the accuracy of the Plexus data, since some fields (e.g., shares outstanding and prices) are contained in both files.

4. Analysis of the trading process

4.1. Summary statistics on institutional trading

Table 1 contains descriptive statistics for the trading universe of the 21 institutions in our sample, grouped by trade direction and by investment style. The unit of observation in this table and all tables that follow is the trade order, i.e., the number of shares of stock the institution decides to buy or sell, not the individual trades in the order. Panels A and B of Table 1 contain the following information for buyer- and seller-initiated orders for three categories of investment strategy: the number of orders, the fraction of orders for exchange-listed securities, the percentage of orders for stocks in three separate market capitalization categories, and the average (volume-weighted) trade price. The table shows that the trading activity for these institutions was substantial. Across all 21 institutions in our sample, 36,590 buy orders and 25,729 sell orders were initiated during the period January 1991 to March 1993. In total, over $83 billion of stocks were purchased or sold by the 21 institutions during this period. The median, across all buy orders for these institutions, of the volume-weighted average trade price is $28.57 for the buys and $31.36 for the sells. About 83% (84%) of the buy (sell) orders were for exchange-listed stocks.

For the entire sample, approximately 16% of the buy orders were in stocks with a market capitalization of less than $200 million (corresponding to the eighth through tenth, or smallest, deciles of market capitalization on the NYSE), 48% were in stocks ranging from $200 million to $2 billion (approximately the fourth through seventh deciles), and 36% were executed in stocks with market capitalization greater than

Table 1
Summary statistics on institutional equity trades

Summary statistics for buyer- and seller-initiated equity trades by 21 institutional investors from January 1991 to March 1993, aggregated by trade direction and investment style. Three styles are represented in the data: technical traders (11 institutions), value-based traders (7 institutions), and index traders (3 institutions). For each investment style, the table reports the number of orders placed in the sample period, the value-weighted percentage of orders in listed stocks, the distribution of orders across three market capitalization categories, the median volume-weighted trade price. The final row of each panel reports the overall median trade price, percentage of orders in listed stocks, distribution across market capitalization categories, and the total number of orders.

			Percentage of orders in stocks with market capitalization			
Investment style	Number of orders	Exchange-listed (%)	≤ \$0.2 bill	> \$0.2 bill and ≤ \$2 bill	> \$2 bill	Volume-weighted trade price
(A) Buyer-initiated trades						
Technical	16,133	76.2%	16.0%	45.3%	38.7%	28.12
Value	6,751	94.4	16.5	33.7	49.8	32.80
Index	13,706	87.9	16.2	58.9	24.9	27.64
Overall	36,590	82.6	16.2	48.2	35.6	28.57
(B) Seller-initiated trades						
Technical	15,553	78.3	14.6	42.2	43.2	28.61
Value	7,463	95.3	14.7	28.9	56.4	35.22
Index	2,713	87.1	5.9	38.0	56.1	35.63
Overall	25,729	84.0	13.7	37.9	48.4	31.36

\$2 billion (approximately the first through third, or largest, deciles). The seller-initiated orders exhibit a similar distribution across market capitalization categories, although it is skewed toward transactions in larger stocks.

Our sample of technical traders contains more orders than the other investment styles. The 16,133 buys (with a total trade volume of \$26 billion) and 15,553 sells (with a total of \$26.3 billion) represent nearly 51% of the total number of orders in our sample. In addition, nearly 24% of the value of these technical trades are in NASDAQ stocks, by far the largest percentage of NASDAQ trades in our sample. On the other hand, the value managers in our sample, with a total trading volume of \$13.3 billion for buys and \$12.4 billion for sells, tended to concentrate their trading in listed stocks. The indexers, whose total trading volume was \$2.8 billion for buys and \$2.4 billion for sells, tended to concentrate their buying activity more in smaller stocks than did the other investment styles. This is mostly due to one small stock index fund that, during our sample period, was almost exclusively buying.

Table 2
Trade size and duration

The table presents the following summary statistics for buyer- and seller-initiated trades for 21 institutional investors, for the period January 1991 to March 1993: the median value of the order, the median number of shares per order, the average number of broker releases per order, the average number of calendar days (or duration) from the first trade to the last trade corresponding to a given order, the median ratio of the trade size (in shares) to the total shares outstanding, expressed in percent, and the average ratio of the number of shares traded to the desired order size (percentage filled). The final row of each panel reports the overall mean (median).

Investment style	Median dollar value of order ($ thousands)	Median number of shares per order (thousands)	Mean number of releases to brokers	Mean trade duration in days	Median ratio of order size to total shares outstanding	Percentage of order filled
(A) Buyer-initiated trades						
Technical	351.3	11.3	2.47	1.50	0.033	95%
Value	475.0	14.0	2.26	2.28	0.041	90
Index	16.1	0.7	1.52	1.93	0.002	100
Overall	138.1	4.8	2.08	1.80	0.011	96
(B) Seller-initiated trades						
Technical	360.7	12.0	2.13	1.43	0.027	96
Value	449.7	11.7	2.11	2.11	0.026	91
Index	367.0	10.0	1.55	1.62	0.015	100
Overall	385.9	11.6	2.06	1.65	0.025	95

Table 2 presents summary information concerning the trading decision for the 21 institutions in our sample, grouped by trade initiation type and by investment strategy. The table contains the median dollar value of the order, the median number of shares traded per order, the mean number of releases to brokers, the mean duration of the order (measured by the number of trade days from the first broker release to the last broker release corresponding to a given order, with one day being the minimum), the median ratio of the order size (in shares) to the total shares outstanding for that stock, and the mean ratio of the number of shares traded to the desired order size (i.e., the percentage of the order filled). Panel A provides information on buyer-initiated trades, where the institutions are grouped by their trading style. Panel B provides the same information for seller-initiated trades.

The table shows that the institutional position adjustments in our sample are large, both in share size and in value, and differ across buys and sells. For example, for buyer-initiated trades, the median order size was $138 thousand and 4,800 shares, while for seller-initiated trades the median order size was $386 thousand and 11,600 shares. Despite these differences, both buy and sell orders were completed in similar fashion, requiring an average of just over two releases to brokers per order. In interpreting this figure, it is important to note that institutions receive only one aggregated report of a broker's trading activity per day. This report includes the total number of shares traded and the average execution price of those shares. Thus, even though several trades may have been executed during the day by a broker in a particular stock, institutions are provided with only one price and volume for that stock for that day. As a result, our estimates of the number of actual trades into which an order was broken will be biased downward.

The duration of trading is closely linked to the number of releases per order. The mean duration for buyer-initiated trades is 1.80 days, for seller-initiated trades the duration is 1.65 days. In turn, duration and the number of releases both appear to be positively related to the ratio of order size to shares outstanding, i.e., difficult trades are spread over a longer period. The position adjustments can represent a substantial fraction of the total shares outstanding; the median value is 0.01% for buys and 0.03% for sells.

Institutional orders were completely filled more than 95% of the time.[5] This result has some bearing on theoretical models, where it is common to assume traders adopt a complex decision rule that specifies the order size as a function of the current price. In practice, however, institutional traders typically select the number of shares to be bought or sold, and brokers or traders then attempt to fill the desired order quantity at the lowest cost in one or more transactions. Specifying a trade quantity, as opposed to a decision rule governing trade execution, is consistent with either the presence of fixed order submission costs, or the lack of feasibility of communicating

[5]This finding is not confined to our sample. Perold and Sirri (1993) examine data on the international trades of a large domestic money management firm, and find that the average completion rate is 96%, a figure very similar to ours.

a complicated dynamic trading strategy to the trading desk. Such a policy may also suggest that market impact costs are small relative to the benefits of completing the order. These results suggest the assumptions underlying theoretical models of trading require closer examination.

There is also discernible variation across investment strategies. For example, some institutions (e.g., the technical traders) have, on average, a greater number of releases to brokers than it takes in days to completely fill the order, indicating that they tend to issue multiple releases to brokers on the same day. Other managers (e.g., the indexers) exhibit a greater trade duration than number of broker releases per order, indicating that one or more days elapse between broker releases for the same order. This result seems inconsistent with the notion that indexers always complete their position adjustments quickly to mirror the changes in the benchmark index. Finally, value managers, whose trades are motivated by fundamental analysis, have longer trade durations and lower fill ratios of approximately 90%.

4.2. Trade motivation

As noted in Section 2, our data contain information on the trade decision date that allows us to investigate whether trades were motivated in part by past price movements. Table 3 presents, for each institution and for buyer- and seller-initiated trades, the market-adjusted average returns one and eight weeks prior to the decision date.[6]

The pre-trade returns are revealing in several dimensions. For some institutions, there is a systematic relation between past excess returns and the trade decision. For example, value managers 4 and 21 tend to buy stocks after they decline. Technical managers 9, 19, and 20 appear to pursue a momentum strategy, while 14 and 15 tend to be contrarian. Further, the market-adjusted returns are economically large for both the eight-week and the one-week pre-trade period, especially for the technical traders. For example, institution 9 bought stocks that had appreciated an average of 9.4% (2.3%) in excess of the market in the eight (one) weeks prior to the trade. Likewise, institution 20 bought stocks that had appreciated an average of 6.5% (0.7%) in excess of the market in the eight (one) weeks prior to the trade. For some institutions, however, there is little evidence of any such dependence. Overall, conditioning trades on past price movements is most common for the technical traders in our sample.

Finally, not only is there heterogeneity across institutions, but also some traders appear to adopt different strategies on the buy and sell sides. For example, institution 15 (a technical trader) is a contrarian on the buy side but does not appear to sell following positive excess returns. The asymmetry between buy- and sell-side

[6] Cross-sectional standard errors are used to determine the statistical significance of these returns. Although we suspect that there may be cross-correlation across observations, we doubt that these correlations will substantially affect our inferences.

Table 3
Pre-decision-date returns associated with common stock trades initiated by 21 institutions from January 1991 to December 1992

The table presents mean market-adjusted pre-trade returns for buyer- and seller-initiated trades for 21 institutions. All returns are adjusted for market movements. The value-weighted CRSP NYSE–AMEX market index is used to adjust the NYSE and AMEX stock trades, and the CRSP NASDAQ index is used to adjust the NASDAQ stock trades. All returns are reported in percent.

	Buy transactions			Sell transactions		
	8 weeks prior to trade	1 week prior to trade	Number of observations	8 weeks prior to trade	1 week prior to trade	Number of observations
(A) Value						
3	1.712	1.053	25	4.370	1.963	30
4	−3.509[a]	−0.940[a]	246	0.326	0.208	321
5	1.146[a]	−1.878[a]	979	−3.585[a]	1.239[a]	1,221
6	−2.795	−0.563	51	4.894	0.527	44
10	−2.323	0.865	29	2.417	−0.229	42
11	0.541	−0.257	2,026	0.631	0.944[a]	2,065
21	−0.708[a]	−0.484[a]	3,312	1.666[a]	0.676[a]	3,653

(B) Technical						
1	1.681[a]	0.105	466	−0.208	0.096	409
7	−0.017	0.123	1,003	1.078	0.847	245
8	0.973	−0.013	587	2.372[a]	0.050	481
9	9.375[a]	2.257[a]	514	6.792[a]	0.123	391
14	−0.933	−1.051[a]	445	1.416[a]	1.667[a]	709
15	−1.261[a]	−0.435[a]	1,306	−0.368	−0.035	1,638
17	2.591[a]	−0.327	657	0.945	0.143	969
19	3.239[a]	0.632[a]	1,429	0.168	0.735[a]	1,228
20	6.538[a]	0.652[a]	4,236	−0.088	0.046	2,929
22	0.298	−0.220[a]	5,343	1.764[a]	0.363[a]	6,406
23	−0.018	−1.020	26	−4.379	−0.270	21
(C) Index						
2	0.256	−0.288[a]	11,299	−1.755[a]	−0.343	764
12	−4.542[a]	−1.220[a]	1,750	3.618[a]	1.111[a]	1,474
13	0.443	−0.062	617	1.761[a]	0.287	467

[a]Significant at better than the 0.01 level.

Table 4

Summary statistics by duration-of-trade category for 21 institutional traders

The table presents, for six trade duration categories: the total number of observations, the mean order size (in thousands of shares), the median ratio of order size to total shares outstanding, the median market capitalization (in billions of dollars) of the shares traded, and the percentage of total trade value for all institutions and for three investment-strategy categories in the period January 1991 to March 1993.

Duration (days)	Frequency	Order size (thousands of shares)	Ratio of order size to shares outstanding	Market capitalization ($ billions)	Percentage of total trade value by investment strategy: All institutions	Value	Technical	Index
(A) Buyer-initiated trades								
1	30,421	30.074	0.009	1.01	57.2%	47.2%	60.3%	76.1%
2	1,754	80.358	0.061	1.36	11.9	6.7	15.5	4.2
3	708	97.331	0.086	1.40	5.3	4.0	6.0	5.1
4	585	97.103	0.104	1.18	4.7	4.6	5.1	1.5
5	551	72.269	0.031	2.07	3.5	3.6	3.4	3.2
6+	2,571	88.899	0.021	1.33	17.4	34.0	9.7	9.8
(B) Seller-initiated trades								
1	21,382	23.878	0.018	1.76	57.8%	48.4%	61.1%	70.3%
2	1,513	48.246	0.069	2.23	11.2	7.9	13.4	3.7
3	572	89.693	0.089	1.56	4.8	4.1	4.9	7.3
4	541	103.101	0.071	2.39	5.1	4.7	5.5	3.2
5	426	160.444	0.085	2.34	4.6	3.4	5.2	3.4
6+	1,295	291.119	0.114	2.06	16.6	31.5	9.9	12.1

behavior is difficult to explain. This could reflect the use of complex, nonlinear trading strategies that are not readily apparent from an examination of the data. In addition, diversity in investment styles suggests that institutional trading can be offsetting. Thus, concerns about the aggregate effects of institutional trading on price volatility may be unfounded.

4.3. *Trade duration*

A key decision for an institutional manager at the execution stage is whether to satisfy desired demand with a single trade, or break up the order into a number of smaller-sized trades to be executed over time. As noted in Section 2, theoretical models suggest that trade duration and the degree of order break-up increase with order size and decrease with liquidity.

Summary Statistics. Table 4 provides summary statistics for buyer- and seller-initiated trades (panels A and B, respectively) for six categories of trade duration. Similarly, Figs. 1 and 2 show the trade duration for buyer- and seller-initiated trades against quintiles of order size (measured relative to total shares outstanding) and market capitalization. The duration of trading is surprisingly short, with almost 83% of buy and sell orders completed within a single day. However, as a proportion of the total value of all transactions in our sample, the orders completed within a day are smaller, 57.2% of the buys and 57.8% of the sells.[7] There are significant differences in trade duration by investment strategy, with indexers far more likely to trade within a day, using a single release, than other traders.

Table 4 suggests that larger-sized trades (measured either by the number of shares traded or by the ratio of shares traded to shares outstanding) tend to involve longer durations for both buyer- and seller-initiated trades, although the relation is not monotonic. It also appears that trades in larger market capitalization stocks are spread over a greater number of days, a finding that appears inconsistent with the hypothesis that trades in less-liquid, i.e., small, stocks take longer to execute. A simple explanation for this result is that order size (and hence trade break-up and duration) increases with market liquidity. Figs. 1 and 2 show, however, that even *within* trade size quintiles (i.e., holding trade size constant) trade duration increases with market capitalization (at least for the two largest trade size quintiles).

An Ordered Response Model of Trade Duration. To investigate the trader's decision more formally, we develop a statistical model for the determinants of trade duration. The discussion in Section 2, as well as the empirical results in Table 4 and Figs. 1 and 2, suggests that the period over which the order is executed (as well as trade break-up) is a function of order size, investment strategy, and market liquidity. From an econometric viewpoint, estimation of this function is complicated because

[7] By contrast, about 61% of the buys and 63% of the sells involve a single release to a broker. As a proportion of the total value of all transactions in our sample, the orders completed with one broker release are smaller, 22% of the buys and 25% of the sells.

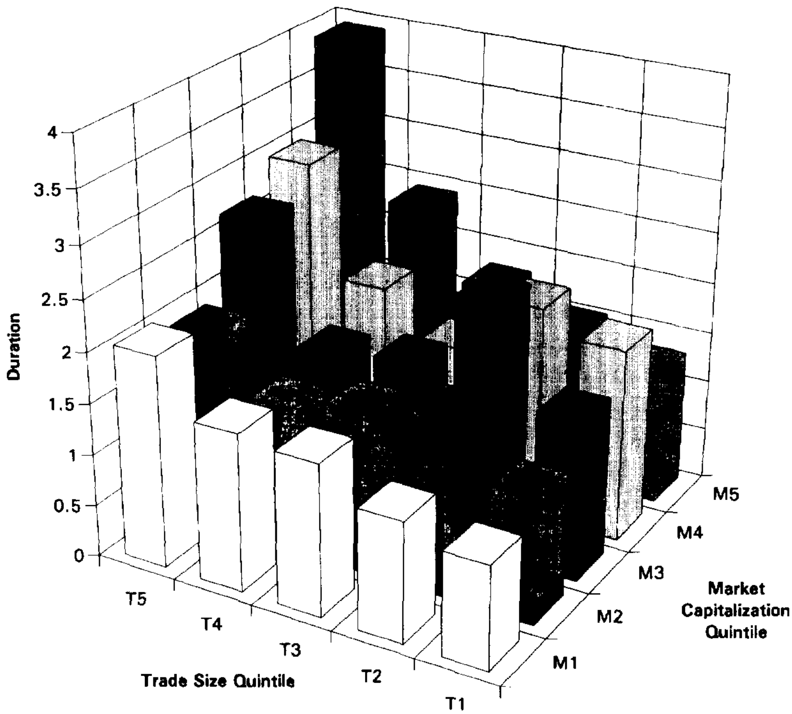

Fig. 1. Trade duration: Buyer-initiated orders.

The figure shows the number of trading days per buy order for quintiles of trade size (defined as the ratio of order size to total shares outstanding) and market capitalization, where T5 and M5 represent the highest trade size and market capitalization quintiles, respectively. The trades are from the period January 1991 to March 1993.

the classical linear model is known to be inadequate for data where the dependent variable assumes a limited range of categories or discrete values, or is qualitative in nature. Accordingly, we estimate an ordered-response model that provides a natural way to represent a dependent variable with values in a narrow range of positive integers.

Formally, let y_i denote the duration of the order i in days, with a maximum of m days. The duration for order i is related to the realization of an unobserved response variable, y_i^*, whose mean is a linear function of a vector of underlying variables. Formally, we write $y_i^* = \beta' x_i + \varepsilon_i$, where β is a vector of coefficients, x_i is a vector of explanatory variables, and ε_i is an error term with zero mean. The location of the realized value of the response variable on the real line determines the duration of the trade. Given m distinct response categories, define $m - 1$ constants

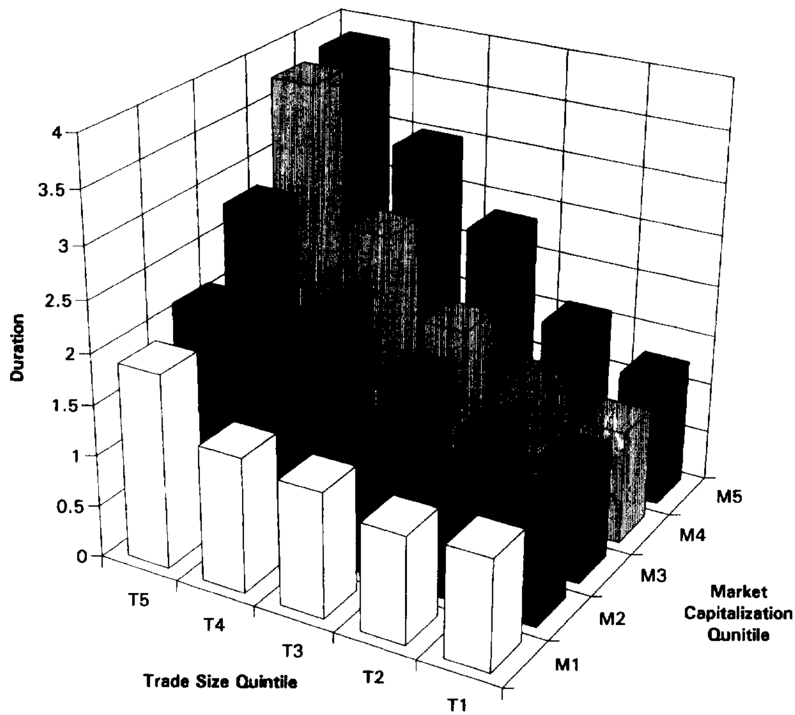

Fig. 2. Trade duration: Seller-initiated orders.

The figure shows the number of trading days per sell order for quintiles of trade size (defined as the ratio of order size to total shares outstanding) and market capitalization, where T5 and M5 represent the highest trade size and market capitalization quintiles, respectively. The trades are from the period January 1991 to March 1993.

$\alpha_1 < \alpha_2 < \cdots < \alpha_{m-1}$. For notational convenience, we define $\alpha_0 = -\infty$ and $\alpha_m = +\infty$. Order i falls in category j ($j = 1, \ldots, m$) if

$$\alpha_{j-1} < y_i^* < \alpha_j \,. \tag{1}$$

We do not observe the underlying response y_i^* or the partitions α_j, but we observe a variable y_{ij}, where $y_{ij} = 1$ if y_i^* falls in category j and zero otherwise. In this case, we set $m = 6$; order i falls in category j if the duration was j and $j \leqslant 5$; otherwise, the order falls in category 6.

From Eq. (1) we obtain:

$$\Pr[y_{ij} = 1 \,|\, x_i] = \Pr[\alpha_{j-1} < \beta' x_i + \varepsilon_i < \alpha_j \,|\, x_i] \,. \tag{2}$$

It follows that

$$\Pr[y_{ii} = 1 | x_i] = F(\alpha_i - \beta' x_i) - F(\alpha_{i-1} - \beta' x_i) \,, \tag{3}$$

where F is the cumulative distribution function of the error term. The probability of observing a particular category then depends on the location of the conditional mean of the underlying response variable, $\beta' x_i$, relative to the partitions α_j. In general, the standard choices for the distribution function F (the logistic and cumulative normal distributions) produce similar results, because outcomes depend on the partition boundaries as well as the distribution function.[8] We report only those estimates using the more familiar ordered probit analysis that relies on the cumulative normal distribution.

The likelihood function for the ordered probit model, given n observations, is

$$L = \prod_{i=1}^{n} \prod_{j=1}^{m} [\Phi(\alpha_j - \beta' x_i) - \Phi(\alpha_{j-1} - \beta' x_i)]^{y_{ij}}, \tag{4}$$

where Φ represents the cumulative standard normal distribution. The parameter estimates are found by maximizing the likelihood function L. For m response categories, there are $m + k - 1$ parameters to be estimated. (There are $m - 1$ partitions, $\alpha_1, \ldots, \alpha_{m-1}$, and k slope coefficients in the vector β. If an intercept is included in the vector β, the first partition is redundant.) Note that the estimated coefficient vector β applies to the underlying continuous response variable, y^*, and not to the discrete duration categories. Information on the relative frequency of the partitions is required to interpret the quantitative significance of the coefficient estimates.

Following the discussion in Section 2, we model the mean of the response variable y_i^* as

$$\beta' x_i = \beta_1 Q_i + \beta_2 b_i Q_i + \beta_3 b_i + \beta_4 logcap_i + \beta_5 D_i^m + \beta_6 D_i^{active} + \beta_7 D_i^{OTC}, \tag{5}$$

where, for order i, Q_i is the ratio of desired order size to shares outstanding, b_i is a dummy variable taking the value one if the order is buyer-initiated and zero otherwise, $logcap_i$ is the log of the market capitalization (in thousands) of the traded stock, a proxy for market liquidity, D_i^m is an investment style dummy variable that equals one if the institution is a technical trader or index fund and zero otherwise, D_i^{active} is an order type dummy variable taking the value one if execution involves market or working orders and zero otherwise, and D_i^{OTC} is a dummy variable taking the value one if the traded stock is NASDAQ-NMS and zero otherwise.

Models of trading predict that β_1 is positive because larger orders take longer to complete. The coefficients β_2 and β_3 measure the incremental volume and fixed effects on the duration of a buyer-initiated order. The coefficient β_4 on market capitalization is predicted to be negative, since trades are executed more slowly in less liquid markets. The coefficient β_5 captures the influence of the institution's trading style. Both index funds and technical traders tend to trade on relatively short-run market momentum, so that we expect $\beta_5 < 0$. The active order dummy controls for order type, and we expect more active orders to be completed more rapidly,

[8] The error term is independently and identically distributed, an assumption that may be violated if orders are correlated.

so that $\beta_6 < 0$. Finally, the nonexchange dummy variable captures any effects on duration attributable to whether the stock was exchange-listed or not. If exchange-listed stocks are more liquid (holding constant market capitalization), we expect $\beta_7 > 0$, because orders in over-the-counter stocks will be broken up more and will take longer to execute.

Results. Table 5 presents the estimates of the five partition boundaries and seven slope coefficients for the probit model, obtained using maximum likelihood, with asymptotic standard errors in parentheses. The table also reports the frequency counts for the six ordered response categories. Order size is significant and the predicted positive relation holds, with $\beta_1 > 0$. The coefficient on the buy interaction term, β_2, is positive and significant, showing that trade duration is longer for buys than for sells, correcting for liquidity and style. Further, as β_3 is also positive and significant, a buyer-initiated trade is likely to take longer.

This result provides new insights into previous empirical evidence suggesting an asymmetric price response for buyer- versus seller-initiated trades.[9] The relative patience of buyers may reflect an underlying asymmetry in the price responses for buyer- versus seller-initiated trades. Price responses may be asymmetric for a variety of reasons that are not considered in current trading models. Asset substitutability suggests that a large buyer-initiated trade in a particular security may be more informationally motivated than a seller-initiated trade. Traders can choose among many potential assets to buy, but when they sell, they usually limit themselves to those assets they already own because of limitations or restrictions on short-sales. Thus, there are very few liquidity motivations for a large-block purchase in a particular stock, but there may be many such reasons for a large sale. Similarly, certain vendors provide information about large stockholders, so there may be better information on the motivations for sells than for buys. For example, a sell order that represents only a fraction of the initiator's known position in that security might be viewed as more liquidity-motivated than a buy order of a similar size originating from a trader without any current holdings in the security.

The relative impatience on the part of sellers may occur for other reasons. Given the decision to sell, a trader who executes a sell order too slowly in the face of declining prices may not be penalized in the same way as a trader who buys too slowly in the face of rising prices. This is because the former represents a (measurable) accounting loss, while the latter represents an (unobservable) opportunity cost. From a behavioral viewpoint, the risks of failing to sell in a declining market may be viewed as greater than the risks of failing to buy in a rising market.

As suggested by Table 4, the coefficient on market capitalization β_4 is positive and significant in Table 5, suggesting that trade duration increases with liquidity. Consistent with Figs. 1 and 2, however, this result does not reflect a positive relation between order quantity and liquidity, because the model also controls for order

[9] Kraus and Stoll (1972), Madhavan and Smidt (1991), and Keim and Madhavan (1994) report evidence of asymmetric price impacts.

Table 5
Estimates of an ordered-response model for trade duration

The table reports estimates of the ordered-probit model

$$\Pr[y_{ij} = 1|x_i] = \Phi(\alpha_j - \beta' x_i) - \Phi(\alpha_{j-1} - \beta' x_i)\,,$$

where y_{ij} equals one if order i results in the jth duration category, α_j is an unknown partition, β is a vector of unknown coefficients, x_i is a vector of independent variables, and Φ is the cumulative normal distribution. Order i falls in category j if the duration (i.e., the number of days to fill the order) was j and $j \leqslant 5$; otherwise, the order falls in category 6. The linear combination $\beta' x_i$ is given by

$$\beta' x_i = \beta_1 Q_i + \beta_2 b_i Q_i + \beta_3 b_i + \beta_4 logcap_i + \beta_5 D_i^m + \beta_6 D_i^{active} + \beta_7 D_i^{OTC}\,,$$

where, for order i, Q_i is the ratio of desired order size to shares outstanding, b_i is a dummy variable taking the value one if the order is buyer-initiated and zero otherwise, $logcap_i$ is the log of the market capitalization of the traded stock, D_i^m is an investment style dummy variable which equals one if the institution is a technical trader or index fund and zero otherwise, D_i^{active} is an order type dummy variable taking the value one if execution involves market or working orders and zero otherwise, and D_i^{OTC} is a dummy variable taking the value one if the traded stock is not exchange-listed and zero otherwise. The maximum likelihood estimates of the partition boundaries and slope coefficients are reported below with asymptotic standard errors in parentheses. The log-likelihood is $-41,762.75$.

α_1	α_2	α_3	α_4	α_5	β_1	β_2	β_3	β_4	β_5	β_6	β_7
1.160[a]	1.402[a]	1.519[a]	1.636[a]	1.756[a]	37.839[a]	11.663[a]	0.103[a]	0.037[a]	−0.390[a]	−0.154[a]	−0.077[a]
(0.065)	(0.004)	(0.005)	(0.006)	(0.007)	(1.816)	(2.835)	(0.013)	(0.004)	(0.013)	(0.028)	(0.015)

Frequency counts for the ordered-response categories

Category	1	2	3	4	5	6
Frequency	50,947	3,196	1,267	1,098	953	3,798

[a]Significant at the 1% level using the Wald χ^2-test.

quantity. This finding is the opposite of what is implied by theoretical models where the price impact per share, and hence the benefit from order fragmentation, is inversely related to overall trading activity. The simplest explanation for this result is that it is more difficult to use passive strategies in thinly-traded stocks, and because passive strategies take longer to execute, trade duration increases with market capitalization. An alternative explanation is that it is easier to conceal the break-up of a large order into smaller components in a liquid stock, although if traders incur reputational costs (see, e.g., Seppi, 1990) by breaking up their orders, this may act as a constraint on order fragmentation. Finally, the number of trades required to fill an order (and hence, the duration of an order) is determined in part by a trade-off between price impact costs and order submission costs. Trade break-up can reduce the overall price impact, but results in higher submission costs. If submission costs decline with market liquidity, the net effect of the trade-off may result in a positive relation between the observed trade duration and market capitalization.

The trading style dummy variable in Table 5 has a significant and negative coefficient, as hypothesized.[10] Further, all else being equal, active strategies are associated with shorter durations, as expected. Finally, the coefficient on the OTC dummy, β_7, is negative, suggesting that trades in OTC stocks tend to have a shorter duration than those of exchange-listed stocks. As with the market capitalization variable, this finding may reflect higher-order submission costs on the OTC market that offset the reductions in price impact from trade break-up. Alternatively, this result could reflect the relative difficulty of placing limit orders (or using crossing systems) in nonexchange-listed stocks.

To help interpret the economic significance of the estimated coefficients, it is useful to consider a specific numerical example. We consider a value trader who wishes to trade 20,000 shares in a NYSE-listed stock with a current market price of \$30 and a market capitalization of \$1.80 billion. These figures are typical of our sample. Using the ordered-probit estimates in Table 5, the probability that this order takes more than one day to complete, using a passive trading strategy, is 27.0% if the trade is seller-initated and 30.6% if it is buyer-initiated. Much of this difference between buys and sells is driven by the fact that traders are more impatient when selling, regardless of size. Using market or working orders results in more rapid execution, and the corresponding probabilities are 22.1% and 25.4%, respectively. By contrast, if the stock is traded on the NASDAQ-NMS system, the probabilities decrease to 19.9% and 23.0%, respectively.

We checked the robustness of our results in several ways. We estimated a Poisson log-linear model, which provides an alternative method of dealing with integer dependent variables. We also estimated the statistical model using the number of releases as the dependent variable. In addition, alternative measures of trade size (including dollar volume, shares traded, and order size relative to average daily

[10] We also estimated a model where we included separate dummy variables for index and technical traders, but the difference in the estimated coefficients on these dummy variables was small.

volume) were used in the estimation. The results from these alternative specifications are very similar to those described above, and are not reported here.

4.4. *Choice of order type*

Four types of orders are also represented in our sample. Ranked from most active to most passive, these order types are: market orders (that specify that the order execute immediately at the current quotes),[11] working orders (which are given to brokers to execute over a period of time to minimize price impacts), crossing orders (where the order is submitted to a trading system such as POSIT or the Crossing Network to be crossed within the prevailing quotes or at a pre-specified price against other institutional orders), and limit orders (which specify prices at which the order will execute).

This ranking is based on the observation that all order types can be represented as price-contingent limit orders. The closer the limit price is to the prevailing bid or ask prices, the more aggressive the order. For example, a market order is simply a limit order to buy at the ask or sell at the bid, while a working order may be viewed as a schedule of limit orders. Similarly, a crossing order is a limit order where the limit price is usually within the prevailing bid–ask quotes. Since a crossing order is more likely to execute (and less likely to offer price improvement) than a limit order whose limit price is set well away from the prevailing quotes, it can be viewed as more active than the traditional limit order.

Summary Statistics. Table 6 presents summary statistics for buyer- and seller-initiated trades (panels A and B, respectively) by order type, for the 21 institutions in our sample. From the table it is evident that the majority of orders (approximately 87% of the total number of orders and 90% of their total value) are executed using market (or market-not-held) orders. The dominance of market orders is surprising, but it is consistent with the high demand for immediacy suggested by our analysis of duration. It is also consistent with the fact that the majority of institutions in our sample are technical traders or indexers.

The four rightmost columns in Table 6 present a breakdown of the choice of order type weighted by the value of the order, for all institutions and by investment strategy. It is clear that there are marked preferences for various types of trading strategies. For example, liquidity-motivated traders such as indexers, who attempt to mimic the behavior of a benchmark index, are more likely to use market orders to maximize correlation with the benchmark. Likewise, information traders with information whose value decays rapidly (e.g., technical traders) desire quick execution and tend to employ market orders. On the other hand, information traders with information whose value decays more slowly (e.g., value traders) are more likely to trade slowly,

[11] Included in the market order category are market-not-held orders, which signify that the market order is subject to limited broker discretion regarding the price and time of execution.

Table 6

Summary statistics on the order type chosen by 21 institutional traders from January 1991 to March 1993

The table presents the frequency, mean order size (in thousands of shares), mean number of broker releases per order, median market capitalization (in billions of dollars), and the percentage of total trade value for all institutions and for three investment-strategy categories, for buyer- and seller-initiated transactions.

Order type	Frequency	Order size (thousands of shares)	Average number of releases per order	Market capitalization ($ billions)	Percentage of total trade value by investment strategy			
					All institutions	Value	Technical	Index
(A) Buyer-initiated trades								
Limit orders	653	98.52	2.71	2.81	4.7%	12.4%	1.3%	0.0%
Crossing networks	523	7.71	1.85	1.34	0.3	0.1	0.4	0.0
Working orders	3,211	34.87	2.46	0.38	5.0	11.3	1.1	11.2
Market orders	31,502	37.66	2.03	1.10	90.1	76.2	97.2	88.8
(B) Seller-initiated trades								
Limit orders	672	88.40	2.65	2.65	4.5%	10.1%	2.2%	0.0%
Crossing networks	113	20.41	1.68	0.84	0.1	0.1	0.2	0.0
Working orders	2,919	33.07	2.43	0.52	5.3	12.2	1.2	11.1
Market orders	21,086	55.86	2.00	2.05	90.1	77.6	96.4	88.9

using less-costly limit and working orders. Finally, with the exception of crossing orders, passive order types tend to be adopted for larger trades.

An Ordered Response Model for Choice of Order Type. To better understand the choice of order type, we need to control not only for investment style, but also for the effects of order size and market liquidity. Let y_i represent the choice of order type, where y_i takes integer values from 1 to 4, corresponding to whether order i was executed using limit orders, a crossing system, working orders, or market orders, respectively. Note y_i has a natural ordering; higher values of y_i correspond to more active trading strategies that are more likely to be executed quickly but are less likely to offer any price improvement. It is important to note, however, that the ranking of y_i is *ordinal* because the distance between categories (or scale) is purely nominal and is of no relevance to our analysis. A desirable statistical model for these data has the property of invariance under the grouping of adjacent response categories, i.e., the conclusions should be unaffected if a new category is formed by combining previously adjacent categories.[12] This property is particularly important for order types where the distinctions between adjacent ordinal categories may be unclear in some cases. For example, the order type field in our data is completed by the trade desk, and it is possible that aggressive working orders are classified as market orders because their execution is virtually assured. Ordered probit is a natural technique to handle potential difficulties of this sort.

Based on the discussion above, we model the choice of order form as determined by the location of an underlying continuous response variable y_i^* whose mean is

$$\beta' x_i = \beta_1 Q_i + \beta_2 b_i Q_i + \beta_3 b_i + \beta_4 logcap_i + \beta_5 D_i^{index} + \beta_6 D_i^{tech} + \beta_7 D_i^{OTC} + \beta_8 absret_i \,, \tag{6}$$

where Q_i is the ratio desired order size to shares outstanding, b_i is an indicator variable taking the value one if the trade is buyer-initiated and zero otherwise, $logcap_i$ is the log of the market capitalization (in thousands) of the stock being traded, D_i^{index} is a dummy variable which equals one if the trading institution is an index fund and zero otherwise, D_i^{tech} is a dummy variable which equals one if the institution is a technical trader and zero otherwise, D_i^{OTC} is a dummy variable taking the value one if the traded stock is not exchange-listed and zero otherwise, and $absret_i$ is the absolute market-adjusted return of the traded stock over the 15 trading days prior to the date of the decision to trade.

In Section 2, we noted theoretical models predict that larger orders in less liquid markets are executed using more passive strategies (so that $\beta_1 < 0$ and $\beta_4 > 0$), and that index and technical traders are more likely to demand immediacy (so that $\beta_5 > 0$

[12] For example, a model for responses to restaurant quality with categories of 'excellent', 'good', 'average', and 'poor' should produce similar conclusions if the 'excellent' and 'good' categories are combined into a new 'very good' category.

Table 7

Estimates of an ordered-response model for choice of order type

The table reports estimates of the ordered-probit model

$$\Pr[y_{ij} = 1 | x_i] = \Phi(\alpha_j - \beta' x_i) - \Phi(\alpha_{j-1} - \beta' x_i),$$

where y_{ij} equals one if order i results in the jth-order type category ($j = 1, \ldots, 4$), α_j is an unknown partition, β is a vector of unknown coefficients, x_i is a vector of independent variables, and Φ is the cumulative normal distribution. The order type categories are limit orders ($j = 1$), crosses ($j = 2$), working orders ($j = 3$), and market orders ($j = 4$). The linear combination $\beta' x_i$ is given by

$$\beta' x_i = \beta_1 Q_i + \beta_2 b_i Q_i + \beta_3 b_i + \beta_4 logcap_i + \beta_5 D_i^{index} + \beta_6 D_i^{tech} + \beta_7 D_i^{OTC} + \beta_8 absret_i,$$

where Q_i is the ratio desired order size to shares outstanding, b_i is an indicator variable taking the value one if the trade is buyer-initiated and zero otherwise, $logcap_i$ is the log of the market capitalization of the stock being traded, D_i^{index} is a dummy variable which equals one if the trading institution is an index fund and zero otherwise, D_i^{tech} is a dummy variable which equals one if the institution is a technical trader and zero otherwise, D_i^{OTC} is a dummy variable taking the value one if the traded stock is not exchange-listed and zero otherwise, and $absret_i$ is the absolute market-adjusted return of the traded stock over the 15 trading days prior to the date of the decision to trade. The maximum likelihood estimates of the partition boundaries and slope coefficients are reported below with asymptotic standard errors in parentheses. The log-likelihood for the model is $-25,314.00$.

α_1	α_2	α_3	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8
0.335[a]	0.515[a]	1.363[a]	3.412	0.758	−0.030	0.117[a]	1.223[a]	1.164[a]	0.271[a]	0.360[a]
(0.069)	(0.007)	(0.012)	(2.920)	(4.346)	(0.015)	(0.005)	(0.019)	(0.016)	(0.018)	(0.121)

Frequency counts for the ordered response categories

Category	1	2	3	4
Frequency	1,307	637	6,118	52,417

[a]Significant at the 1% level using the Wald test.

and $\beta_6 > 0$).[13] As before, β_2 and β_3 capture the incremental effects associated with buyer-initiated trades. We expect the coefficient of the OTC dummy variable, β_7, to be positive because the organized exchanges (which, unlike NASDAQ, operate through an auction mechanism) offer the possibility of price improvement within the quotes, making the use of passive strategies more attractive. Finally, the coefficient of the previous return, β_8, captures the effect of market momentum (and volatility) on the choice of order type. Limit orders can be thought of as options, and the value of the option given to the market when placing a limit order increases with market volatility. Thus, we expect that larger absolute prior returns should reduce the use of passive strategies. Further, for a technical trader, a large momentum may dictate the use of market orders over slower and less certain strategies, such as crossing orders. Both arguments suggest that $\beta_8 > 0$.

Results. Table 7 reports the estimates of the partition boundaries and slope coefficients for the probit model, obtained using maximum likelihood, with asymptotic standard errors in parentheses. Surprisingly, the order size coefficients are not significantly different from zero. However, the buy indicator has a negative sign and is significant at the 10% level, suggesting a tendency for buy orders to be executed more passively. These results may reflect a lack of statistical power because the sample is primarily composed of market orders. Alternatively, order size may be less of a determinant of order type than might be thought. (The general lack of significance of order size is also present when alternative definitions of size, e.g., dollar volume, are used.) The coefficient of market capitalization is positive, suggesting that more active strategies are likely to be employed in more liquid stocks, correcting for differences across markets. This is important, because it shows that our earlier result showing a positive relation between trade duration and market liquidity does not simply reflect the increased use of passive strategies in more liquid stocks.

The investment style variables have the correct (positive) sign and are significant; both technical and index traders are more likely to use active strategies than value managers. The positive sign on the OTC dummy variable shows that, all other factors being equal, orders for exchange-listed stocks are more likely to be executed using passive strategies. As noted above, this may reflect the relative ease of using passive strategies in auction markets, which offer the possibility of price improvement. Our findings regarding the use of active strategies for NASDAQ-NMS stocks is also consistent with the fact that trade duration is shorter in these stocks, as reported in Table 5. Finally, the market momentum coefficient is positive and significant, as expected. Active orders are more likely to be used in stocks where momentum is high.

[13]There is greater heterogeneity among traders in the choice of orders, so that we include two style dummy variables.

5. Conclusions

Despite the importance of institutions in the U.S. equity market, there have been few academic studies of their trading motivations and the process by which they execute their orders. This study attempts to fill some of the gaps in our understanding of institutional trading, and in doing so, to test the predictions of theoretical models of trader behavior.

We examine empirically the behavior of institutional traders, using data on the complete equity transactions of 21 institutions in various subperiods from 1991–1993. The institutions in our sample differ widely in their trading styles and motivation for trade. For some institutions, there is a significant relation between the buy–sell decision and past excess returns, while for others there is no apparent relation. The overall effect of this behavior might be offsetting because some traders are contrarians while others follow trends. Surprisingly, some institutions behave asymmetrically in terms of their motivation for buys versus sells.

As expected, trade duration increases with order size. However, we find that trade duration increases with market liquidity, holding constant order size, possibly because it is easier to conceal a sequence of subtrades in a highly active stock than it is in an illiquid stock. Further, although buy and sell transactions are treated symmetrically in theoretical models, our results suggest that institutional traders tend to spread buy orders over longer periods than equivalent sell orders. We also find significant differences in the choice of order type across institutional styles. In general, though, the institutions in our sample show a surprisingly strong demand for immediacy, even in those institutions whose trades are based on relatively long-lived information. Consequently, it is rare that an order is not entirely filled. One explanation for this result is that institutions believe their information is short-lived. Alternatively, the costs of passive strategies, especially the opportunity costs of failing to execute an order in a timely manner, are possibly higher than previously thought.

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