

**ANATOMY OF THE TRADING PROCESS:  
EMPIRICAL EVIDENCE ON THE BEHAVIOR OF  
INSTITUTIONAL TRADERS**

by

**Donald B. Keim  
Ananth Madhavan**

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**RODNEY L. WHITE CENTER FOR FINANCIAL RESEARCH  
The Wharton School  
University of Pennsylvania  
Philadelphia, PA 19104-6367**

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Donald B. Keim  
and  
Ananth Madhavan\*

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# Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders

## **Abstract**

This paper examines empirically the behavior of institutional traders using unique data on the equity transactions of 21 institutions of differing investment styles during 1991-1993. The data provide a detailed account of the anatomy of the trading process, and include information on the number of days needed to fill an order and types of order placement strategies employed. We analyze the determinants of trade duration and the decisions regarding order type. Our analysis provides some support for the predictions made by theoretical models, but suggests that these models fail to capture important dimensions of trading behavior.

# 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.<sup>1</sup> A number of recent studies (Chan and Lakonishok (1993a, 1993b) and Keim and Madhavan (1992)) have focused on the price movements associated with institutional trades.<sup>2</sup> However, despite their importance in trading volume, relatively little is known about the actual trading behavior of institutional investors.

There are several reasons to focus on the trading behavior of this important group of equity market participants. Institutional traders, if faced with potentially very large position changes, may spread their trades over several days, and their continued presence on one side of the market may have an important effect on asset price dynamics. Further, if institutional traders initiate changes in their portfolio positions following abnormal price movements, their collective actions may stabilize prices if they follow contrarian strategies or exacerbate stock volatility if they do the opposite. Second, institutions' choice of order type may have important effects on market liquidity and execution costs. To the extent institutions rely on active strategies based on market orders, they act as demanders of liquidity. By contrast, if they rely on passive 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 rational trading behavior remain largely untested. As 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.

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<sup>1</sup>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 73.3% of the value of trading on the London Stock Exchange, and 76.6% of share volume on the Tokyo Stock Exchange.

<sup>2</sup>See also the Securities and Exchange Commission (1971) for one of the first studies of institutional trading. In addition, there is a large literature on the price impacts of large-block trades, some, perhaps most, of which were initiated by institutions. See, among others, Kraus and Stoll (1972), Scholes (1972), and Holthausen, Leftwich, and Mayers (1987, 1990).

This paper analyzes empirically the trading of institutions in an effort to fill some of the gaps in our understanding of their trading behavior. Our data, the transaction history of the equity trades of 21 institutions during the period 1991 to 1993, differ from those used in other studies in several important respects. First, the data indicate when the trading decision was made, and the desired number of shares at that time. When institutions trade, there is often a delay (possibly more than a day) between the decision to trade and the first transaction associated with that decision, disassociating the transaction(s) from their original motivation. Thus, it is difficult to infer from available data sources, such as the widely-used data from the Institute for the Study of Securities Markets (ISSM), the possible motivations for an observed transaction or a series of transactions. With our data, there is no such ambiguity; we know precisely the magnitude and the timing of the latent or unexpressed demands underlying the trade.

Second, unlike virtually all other transaction-level data, we have a complete record of all the trade activity generated by a particular indicated desire to trade. This information is important because an order for a certain number of shares is often broken up into several trades spanning many different and not necessarily adjacent days. If the separate order partitions precipitated by a single order cannot be uniquely identified, it is not possible to analyze trading decisions.<sup>3</sup>

Third, our data identify the type of order (e.g., market order, limit order, etc.) associated with the trade. Financial economists have only recently started to examine the effects of strategic decisions over order type on liquidity and prices. Most transaction level databases do not identify the type of order used to execute a trade. Since there may be important differences in the price impacts and speed of execution across order type (e.g., using market orders assures execution but may induce large price impacts, while using limit orders can lead to price improvement but runs the risk of non-execution), this data is necessary to make an informed analysis of trader behavior.

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<sup>3</sup>Chan and Lakonishok (1993a) use SEI data on institutional trades to aggregate trading activity across days into an order or 'package' by assuming that successive trades by an institution within a five day window are generated by the same order. The accuracy of this assumption is unclear.

Fourth, the data identify the trade as buyer- or seller-initiated. In most available databases, and therefore most of the research in this area, volumes are not signed and the trade initiation must be inferred indirectly using time-stamped quotation data. There are several recent exceptions. Keim and Madhavan (1992) examine institutional trades of large blocks of stock using data that not only permits identification of whether the trade was a buy or sell, but also who initiated the trade. Chan and Lakonishok (1993b) also examine the transactions of institutional investors and can ascertain whether a trade was a buy or sell. However, the information in their data does not permit identification of 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.

Finally, our data set is large; we have information on over 62,000 recent institutional orders (which usually are broken up) with a total value of over \$83 billion. Further, a wide variety of institutions are represented in the sample, and we have information on their investment styles (e.g., indexers, value managers, technical analysts). The data permit tests of detailed hypotheses regarding the 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. Our results do not suggest a consistent relation between past returns and the buy-sell decision, even for those institutions identifying themselves as technical traders. Rather, for the institutions in our sample, trade appears to be motivated by exogenous factors which seem to outweigh any association with prior returns. We then examine the process by which the desired demands are translated into executed trades. As predicted by most theoretical models, larger order quantities are associated with longer trading durations. However, the duration of trading increases with market capitalization, holding constant order size. Overall, though, the duration of trading is surprisingly short, indicating a high demand for immediacy. Finally, we find that buys take longer to execute than equivalent-sized sells, which is consistent with a larger price impact for buys versus

equivalent sells. This finding sheds light on previous empirical research which finds that the majority of large block trades are seller-initiated (e.g., Kraus and Stoll (1972), Keim and Madhavan (1992)).

Turning to the decision over order type, we find that larger buy orders are more likely to be executed using passive strategies, but there is no such relation for seller-initiated trades. In conclusion, although our findings provide direct confirmation of the predictions of simple theoretical models of the trading process, they also suggest that these models fail to incorporate the true richness of the trading process.

The paper is organized as follows: Section 2 describes the hypotheses regarding the trading process to be analyzed empirically; Section 3 describes our data sources; Section 4 presents an empirical analysis of the trading process; and Section 5 summarizes our main findings.

## 2 Empirical Hypotheses

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

### *The Motivation for Trade*

Institutional trades result from the desire of those institutions to adjust their portfolio positions. In theoretical models of trading such position adjustments may arise because traders possess private information or (perhaps more reasonably for institutions) may reflect liquidity motivations unrelated to private information.<sup>4</sup> Unfortunately, there is little theoretical guidance regarding non-information motives for trading.

Some institutional position adjustments are determined largely by exogenous factors. For example, trades may be induced by lumpy infusions (withdrawals) of cash, along with an institution's reluctance to hold large cash balances. Similarly, the trades of a mutual fund may be driven largely by the cash inflows and withdrawals of individual investors. These exogenous cash flows (and thus institutional trades) may be systematically related

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<sup>4</sup>See, e.g., Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987).

to past returns.

Position adjustments may 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, an institution’s trades may be determined primarily by its objectives or trading style. 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.

Other traders use technical trading strategies which 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 or future performance is of some importance, since positive feedback strategies exacerbate short-run price volatility while negative feedback strategies have the opposite effect. We can investigate this issue because our data indicate that actual date of the decision to trade as well as the dates of the individual transactions corresponding to the order.

#### *Trade Duration and Order Breakup*

In most dynamic microstructure models (e.g., Kyle (1985), Foster and Vishwanathan (1990), and 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 can reduce the overall price impact of a large order by breaking it up into several smaller trades.

Microstructure models (e.g., Kyle (1985)) also implicitly predict that the benefits



from spreading a trade over a longer duration are greatest for thin markets. In such markets, price impacts are large because market makers' inventory control costs are high or asymmetric information is severe. These considerations imply that correcting for order size, trade duration should decrease with market liquidity.

### *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.<sup>5</sup> Theoretical models where traders make strategic decisions about order type (see, e.g., Keim and Madhavan (1993)) suggest a trade-off between active and passive strategies. Active strategies using 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.

Thus, active managers trading on information that is short-lived (e.g., technical traders whose decisions are based on momentum) should 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 and may prefer to trade more discreetly, using working or limit orders. Keim and Madhavan (1993) also predict that passive strategies will be adopted by managers with large orders, for whom the price impact associated with market orders would far outweigh the opportunity costs associated with non-execution. Their model suggests that the benefits of a passive strategy are greatest in thin markets where liquidity is low and price impacts are large.

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<sup>5</sup>In many microstructure 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 (1989), Angel (1991), and Kumar and Seppi (1993) present models of limit orders; Keim and Madhavan (1993) examine the choice between active and passive strategies; and Handa and Schwartz (1991), Harris and Hasbrouck (1992) examine empirically the differences in the price effects of limit and market orders.

Before turning to the analysis of these hypotheses, we first describe the data.

### 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 the equity transactions of 21 institutions for various subperiods during the period January 1991 to March 1993. The institutions (which are identified to us only by number to preserve confidentiality) include investment managers, indexers, and pension funds, and differ in their motivations for trade, their trading styles, and the stocks traded. The structure of the data proves important in our subsequent empirical work, and accordingly we discuss this in some detail. Among other items, the data contain the following information that we use in our analysis of the transaction process:

- (i) the institution or manager initiating the trade;
- (ii) the date when the trading decision was made;
- (iii) the cusip number of the stock to be traded;
- (iv) the desired number of shares to be traded with a buy-sell indicator;
- (v) the closing price on the day before the decision to trade;
- (vi) the dates and number of desired shares corresponding to releases from the institution's trade desk to the brokers who will fill the trade;
- (vii) 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;
- (viii) 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);
- (ix) several additional fields that identify the average daily volume of transactions in the security, the market capitalization of the security, and an indicator for whether the stock was listed on an exchange or traded over-the-counter.

In addition, 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); 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.)

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 felt 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 price and return information from the files obtained from 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 and returns over several multi-week intervals before the trade. We also used the CRSP data to verify the accuracy of the Plexus data since some fields (e.g., shares outstanding and prices) are represented in both files.

We turn now to an analysis of the empirical predictions made in Section 2.

## **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 that follow is the trade order, the number of shares of stock the institution decides to buy or sell, and not the individual trades in the order.

Panels A and B of table 1 contains the following information for buyer- and seller-initiated orders for three categories of investment strategies: 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-March 1993. In total, over \$83 billion of stocks were purchased or sold by the 21 institutions over the 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 to 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 \$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 slightly more skewed toward transactions in larger stocks.

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

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 mean dollar value of the order, the mean 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 1 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, while 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 initiation type. For example, for buyer-initiated trades, the average value of an order was \$1.15 million for 34,800 shares, while for seller-initiated trades the average order value was \$1.60 million for 48,400 shares.

Despite these differences, both buy and sell orders were completed in similar fashion, requiring just over 2 releases to brokers per order on average. In interpreting this figure, it is important to note that institutions receive only one aggregated report of a broker's trading activity per day which 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 and 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. This result has

some bearing on theoretical models where it is common to assume traders adopt a decision rule specifying the order size as a function of the current price. In practice, however, institutional traders first decide on 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.<sup>6</sup> Specifying a trade quantity, as opposed to a trading rule, may be consistent with the presence of fixed order submission costs or the lack of feasibility of communicating a complicated dynamic trading strategy to the trading desk. Since this assumption affects trader behavior and hence transaction prices, it bears closer examination.

There is also discernable 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 may transpire 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, which allows us to investigate whether trades were motivated in part by past price movements. Table 3 presents, for buyer- and seller-initiated trades and the three categories of investment strategy, the value-weighted mean returns for one, two, four and eight weeks prior to the decision date. There is no evidence of a systematic relation between past price movements and the buy-sell decision, and the magnitude of the returns is small in relation to the standard errors. This conclusion appears to hold for a range of pre-trade horizons,

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<sup>6</sup>Under some circumstances, the decision is altered during the trading process. In general, however, this is relatively uncommon in our sample.

and across all three styles. The pattern for the unweighted returns is very similar.

Oddly, there is little evidence of a systematic relation even for those institutions describing themselves as technical traders. One explanation for this finding is that institutions in this category use a variety of trading rules, possibly of a conflicting nature, so that there appears to be no systematic relation at the aggregate level. However, we do not find any evidence of systematic pre-trade price movements for any of the individual institutions. The motivation for institutional position adjustments is not easily explained by past price movements.

### 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, we expect trade duration and the degree of order break-up to increase with order size and liquidity.

Table 4 provides summary statistics for buyer- and seller-initiated trades (Panels A and B, respectively) for six categories of trade duration. Similarly, figures 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.<sup>7</sup> 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

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<sup>7</sup>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.

is 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 breakup and duration) increases with market liquidity.

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 figures 1 and 2, suggests that the period over which the order is executed (as well as trade breakup) is a function of order size, investment strategy, and market liquidity. From an econometric viewpoint, estimation of this function is complicated because 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 that takes 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,  $y_i^*$ , which is a linear function of a vector of underlying variables,  $y_i^* = \beta'x_i + \epsilon_i$ . The location of this response variable on the real line determines the duration of the trade. Given  $m$  distinct response categories, define  $m - 1$  constants  $\alpha_1 < \alpha_2 < \dots < \alpha_{m-1}$ . For notational convenience, we define  $\alpha_0 = -\infty$  and  $\alpha_m = +\infty$ . Order  $i$  falls in category  $j$  ( $j = 1, \dots, m$ ) if:

$$\alpha_{j-1} < y_i^* < \alpha_j. \quad (1)$$

We do not observe the underlying response  $y_i^*$  or the partitions  $\alpha_j$ , but we observe a variable  $y_{ij}$ , where  $y_{ij} = 1$  if  $y_i^*$  falls in category  $j$  and 0 otherwise. In this case, we set  $m = 6$ ; order  $i$  falls in category  $j$  if the duration was  $j$  and  $j \leq 5$ ; otherwise, the order falls in category 6.

From equation (1) we obtain:

$$\Pr\{y_{ij} = 1|x_i\} = \Pr[\alpha_{j-1} < \beta'x_i + \epsilon_i < \alpha_j|x_i], \quad (2)$$



It follows that:

$$\Pr[y_{ij} = 1|x_i] = F(\alpha_j - \beta'x_i) - F(\alpha_{j-1} - \beta'x_i), \quad (3)$$

where  $F$  is the cumulative distribution function of  $\epsilon$ . The probability that a particular order type is chosen depends on the location of the conditional mean of the underlying response variable relative to the partitions. Given the conditional mean  $\beta'x_i$ , the probability of a given outcome depends on the partitions  $\alpha_j$ . Thus, the particular distributional assumptions on the error term is not crucial in determining the probabilities assigned to various choices. In general, the standard choices for the distribution function  $F$  (the logistic and cumulative normal distributions) produce similar results, and we report only the estimates using the more familiar ordered probit analysis which relies on the cumulative normal distribution.

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

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

where  $\Phi$  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,  $\alpha_1, \dots, \alpha_{m-1}$ , and  $k$  slope coefficients in the vector  $\beta$ ).<sup>8</sup> Note that the estimated coefficient vector  $\beta$  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 threshold level,  $y_i^* = \beta'x_i$ , as:

$$y_i^* = \beta_1 Q_i^b + \beta_2 Q_i^s + \beta_3 MCap_i + \beta_4 D_i^{index} + \beta_5 D_i^{tech} + \beta_6 D_i^{OTC}$$

where  $Q_i^b$  ( $Q_i^s$ ) is the ratio of order size to shares outstanding for buyer-initiated (seller-initiated) trades,  $MCap_i$  is the market capitalization of stock  $i$  (in billions of dollars),  $D_i^{index}$  is an investment style dummy variable which equals 1 if the trading institution is an

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<sup>8</sup>If an intercept is included in the vector  $\beta$ , the first partition is redundant.

index fund and zero otherwise,  $D_i^{tech}$  is an investment style dummy variable which equals 1 if the institution bases their trades in part on prior price movements and 0 otherwise, and  $D_i^{OTC}$  is a dummy variable taking the value 1 if the stock is traded over-the-counter and 0 otherwise.

Microstructure models predict that  $\beta_1$  and  $\beta_2$  are positive because larger orders result in longer durations. Similarly, the coefficient  $\beta_3$  on market capitalization is predicted to be negative since trades are executed more slowly in less liquid markets. The coefficients  $\beta_4$  and  $\beta_5$  capture the influence of the institution's trading style. Since indexers trade quickly using market orders to closely track a particular index, we expect  $\beta_4 < 0$ . Similarly, technical traders also tend to trade on relatively short-run market momentum, so that we expect  $\beta_5 < 0$ . The OTC 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),  $\beta_6 > 0$  because orders in over-the-counter stocks will be broken up more and will take longer to execute.

Table 5 presents the estimates of the 5 partition boundaries and 6 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. Both order-size variables are significant and the predicted positive relation holds. The difference in the magnitudes of the coefficients for the order-size variable for buys versus sells suggests that trade duration is longer, correcting for liquidity and style, for buys than for sells. To test the null hypothesis that equivalent buy and sell volumes have similar durations, we also estimated the model under the joint coefficient restriction  $\beta_1 = \beta_2$ . Define by  $L_r$  the value of the likelihood function evaluated under the restrictions imposed on the model. Then,  $\lambda = -2 \ln(\frac{L_r}{L})$  is distributed as a  $\chi_m^2$ , where  $m$  is the number of restrictions imposed. From Table 5,  $\lambda = 17$ , so that the null hypothesis that both buy and sell volumes have identical durations is rejected at below the 1% significance level.

This result provides new insights into previous empirical evidence suggesting an asym-

metric price response for buyer- versus seller- initiated trades.<sup>9</sup> The relative patience of buyers may reflect and reinforce an underlying asymmetry in the price responses for buyer- versus seller-initiated trades. Price responses may be asymmetric for a variety of reasons. A large buyer-initiated trade in a particular security is more likely to be informationally motivated than a seller-initiated trade because of asset substitutability. Traders can choose among many potential assets to buy, but usually limit themselves to those assets they already own when selling. Further, public information regarding institutional holdings may provide a source of asymmetry. Since information regarding institutional security holdings is available, there may be better information on the motivations for sells than for buys. For example, a large institutional sale may represent only a fraction of the initiator's (known) position in that security. This trade may be regarded as more likely to be liquidity-motivated than a large buy order from an institution without an existing position 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 so-called "fear factor" cited by many traders may offer an explanation for the asymmetry in duration and breakup for buys versus sells. The key point to note, however, is that when traders take longer to execute buy orders than equivalently-sized sell orders, their behavior implies an asymmetric market response for buy versus sell orders. Intuitively, if buyers are more patient than sellers, the market imputes a larger order size to a buy trade (and hence will induce a larger quote revision) than an equivalent sell trade.

Consistent with table 4, the coefficient on market capitalization  $\beta_3$  is positive and significant in table 5, suggesting that trade duration increases with liquidity. However, this result does not reflect a positive relation between order quantity and liquidity be-

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<sup>9</sup>See, e.g., Kraus and Stoll (1972), Madhavan and Smidt (1991), and Keim and Madhavan (1992).

cause order size is being kept constant. This finding is contrary to the predictions of most microstructure models. Keim and Madhavan (1993) provide an explanation for why duration may (other things equal) increase with market liquidity. They develop a model of trading where order size, order type, and trade duration are endogenously determined. In their model, trade breakup (and hence duration) is positively related to order size. Further, the number of trades required to fill an order is determined in part by a trade off between price impact costs and order submission costs. Trade breakup 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 between these two cost components can result in a positive relation between breakup (or equivalently duration) and market capitalization. An alternative explanation is that it is more difficult to use passive strategies in thinly-traded stocks. As passive strategies take longer to execute, trade duration may increase with market capitalization. We show below that this explanation is not correct.

The trading style dummy variables in table 5 have significant negative coefficient estimates, as hypothesized. Finally, the coefficient on the OTC dummy,  $\beta_6$ , is negative, suggesting that trades in OTC stocks tend to have shorter durations than those of exchange listed stocks. As with the market capitalization variable, this finding may reflect higher order submission costs on the OTC market which offset the reductions in price impact from trade breakup. Alternatively, this result could reflect the relative difficulty of placing limit orders (or using crossing systems) in non-exchange listed stocks.

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. The results from these alternative specifications are very similar to those described above, and are not reported here.

We turn now to an analysis of the trader's choice of order type.

#### 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 (specifying that the order execute immediately at the current quotes)<sup>10</sup>; 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 orders types can be represented as price-contingent limit orders. The closer the limit price is to the prevailing bid and 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.

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 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 consist of 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.

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<sup>10</sup>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.

It is clear that there are marked preferences for various types of trading strategies. For example, liquidity-motivated traders like 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 that rapidly decays in value (e.g., technical traders) desire quick execution and tend to employ market orders. On the other hand, information traders with information that has a longer half-life (e.g., value traders) are more likely to trade slowly, using limit and working orders that are less costly. Finally, with the exception of crossing orders, passive order types tend to be adopted for larger trades.

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.<sup>11</sup> This property is particularly important for order type 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

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<sup>11</sup>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.

the location of an underlying continuous response level  $y_i^*$  as:

$$y_i^* = \beta_1 Q_i^b + \beta_2 Q_i^s + \beta_3 MCap_i + \beta_4 D_i^{index} + \beta_5 D_i^{tech} + \beta_6 D_i^{OTC} + \beta_7 R_i$$

where  $Q_i^b$  ( $Q_i^s$ ) is the ratio of order size to shares outstanding for buyer-initiated (seller-initiated) trades,  $MCap_i$  is the market capitalization of stock  $i$  (in billions of dollars),  $D_i^{index}$  is an investment style dummy variable which equals 1 if the trading institution is an index fund and zero otherwise,  $D_i^{tech}$  is an investment style dummy variable which equals 1 if the institution bases their trades in part on prior price movements and 0 otherwise,  $D_i^{OTC}$  is a dummy variable taking the value 1 if the stock is traded over-the-counter and 0 otherwise, and  $R_i$  is the absolute value of the return for the traded stock over the 10 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  $\beta_1 < 0$ ,  $\beta_2 < 0$  and  $\beta_3 > 0$ ), and that index and technical traders are more likely to demand immediacy (so that  $\beta_4 > 0$  and  $\beta_5 > 0$ ). We expect the coefficient of the OTC dummy variable,  $\beta_6$ , to be positive because exchange markets such as the NYSE are auction markets and offer the potential for price improvement within the quotes. Further, Nasdaq is organized as a dealer market making it more difficult to execute passive strategies using limit orders. Finally, the coefficient of the previous return,  $\beta_7$ , 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  $\beta_7 > 0$

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. The results offer some support for theoretical models of trader behavior. Larger buy orders are more likely to be executed using passive strategies. However, there

is no corresponding relation for seller-initiated trades.<sup>12</sup> This result is suggestive of a perception among institutional traders that buys are more difficult or costly to execute than equivalent sells, which is consistent with our results for trade duration.

The coefficient of market capitalization is positive suggesting that more active strategies are likely to be employed in more liquid markets. This is important because it indicates 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 indicates that orders for exchange-listed stocks are more likely to be executed using passive strategies, all other factors being equal. 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 OTC stocks is also consistent with the fact that trade duration is shorter in OTC stocks as reported in table 5. Finally, the market momentum coefficient is positive, as expected, and is significant at the one percent level. Active orders are more likely to be used in stocks where momentum is high.

## 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, 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. As

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<sup>12</sup>The coefficient  $\beta_1$  is negative and is significant at the 5% level, while the coefficient of  $\beta_2$  is not significantly different from zero. However, a likelihood ratio test indicates that the difference between the two coefficients is not significant.



expected, trade duration and breakup increase with order size, but these variables also increase with market liquidity. Further, although buys and sells are symmetric in current theoretical models, our results indicate that institutional traders tend to execute buy orders over longer durations than equivalent sell orders.

We find, as expected, that larger buy orders in thinner markets are executed using more passive strategies. However, there is no such relation for sell orders, again suggesting an asymmetry in the perception of the price impacts of buy versus sell orders. There are significant differences in the choice of order type by institutional style. In general, however, institutions also show a surprisingly strong demand for immediacy, even for those traders 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 may be higher than previously thought.

In summary, our results validate some of the predictions of theoretical models but show that these models fail to capture important dimensions of the trading process and trader behavior.

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Table 1

## Summary Statistics on Institutional Equity Trades

Panels A and B report summary statistics for buyer- and seller-initiated equity trades by 21 institutional investors from January 1991 to March 1993, aggregated by 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, the overall percentage of orders in listed stocks, the overall distribution across market capitalization categories, and the total number of orders.

Investment Style	Number of Orders	Exchange Listed (%)	Percentage of orders in stocks with market capitalization:			Volume-Weighted Trade Price
			≤ \$0.2 bill	> \$0.2 bill and ≤ \$2 bill	> \$2 bill	
<i>A: Buyer-initiated Trades</i>						
Technical	16,133	76.2	16.0%	45.3%	38.7%	28.12
Value	6751	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
<i>B: Seller-initiated Trades</i>						
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

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 average value of the order; the average 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	Mean Dollar Value of Order (\$ thousands)	Mean 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 (%)
<i>A: Buyer-initiated Trades</i>						
Technical	1,609.6	50.5	2.47	1.50	0.033	94.93
Value	1,967.5	55.4	2.26	2.28	0.041	90.02
Index	207.2	6.3	1.52	1.93	0.002	100.00
Overall	1,150.3	34.8	2.08	1.80	0.011	95.92
<i>B: Seller-initiated Trades</i>						
Technical	1,690.0	54.5	2.13	1.43	0.027	96.11
Value	1,665.6	44.7	2.11	2.11	0.026	90.85
Index	885.8	23.8	1.55	1.62	0.015	99.93
Overall	1,598.1	48.4	2.06	1.65	0.025	94.99

**Table 3****Pre-Decision Date Returns for Trades Initiated  
by 21 Institutions from January 1991-March 1993**

The table presents, for buyer- and seller-initiated trades and for three investment-strategy categories the mean returns (weighted by the value of the order) 1, 2, 4, and 8 weeks prior to the trade decision date, with standard errors in parentheses.

Investment Style	Pre-trade Return 8 weeks	Pre-trade Return 4 weeks	Pre-trade Return 2 weeks	Pre-trade Return 1 weeks
<i>A: Buyer-initiated Trades</i>				
Technical	0.047 (0.164)	0.023 (0.113)	0.007 (0.080)	0.003 (0.059)
Value	0.018 (0.132)	0.002 (0.094)	-0.003 (0.068)	-0.006 (0.052)
Index	0.030 (0.139)	0.002 (0.098)	0.001 (0.070)	0.001 (0.053)
<i>B: Seller-initiated Trades</i>				
Technical	0.030 (0.172)	0.024 (0.117)	0.012 (0.086)	0.008 (0.063)
Value	0.024 (0.132)	0.016 (0.095)	0.014 (0.072)	0.011 (0.053)
Index	0.037 (0.142)	0.019 (0.097)	0.009 (0.068)	0.005 (0.053)

**Table 4**  
**Summary Statistics by Duration-of-Trade Category**  
**for 21 Institutional Traders**

The table presents, for 6 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
<i>A: Buyer-initiated Trades</i>								
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
<i>B: Seller-initiated Trades</i>								
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



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 1 if order  $i$  results in the  $j$ th duration category,  $\alpha_j$  is an unknown partition,  $\beta$  is a vector of unknown coefficients,  $x_i$  is a vector of independent variables, and  $\Phi$  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  $j \leq 5$ ; otherwise, the order falls in category 6. The linear combination  $\beta'x_i$  is given by:

$$\beta'x_i = \beta_1 Q_i^b + \beta_2 Q_i^s + \beta_3 MCap_i + \beta_4 D_i^{index} + \beta_5 D_i^{tech} + \beta_6 D_i^{OTC}$$

where  $Q_i^b$  ( $Q_i^s$ ) is the ratio of desired order size to shares outstanding for buyer-initiated (seller-initiated) trades ( $\times 10^{-2}$ ),  $MCap_i$  is the market capitalization of stock  $i$  (in \$bill),  $D_i^{index}$  is an investment style dummy variable which equals 1 if the trading institution is an index fund and zero otherwise,  $D_i^{tech}$  is an investment style dummy variable which equals 1 if the institution bases their trades in part on prior price movements and 0 otherwise, and  $D_i^{OTC}$  is a dummy variable taking the value 1 if the stock is traded over-the-counter and 0 otherwise. The maximum likelihood estimates of the partition boundaries and slope coefficients are reported below with asymptotic standard errors in parentheses.

	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_5$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	$\beta_6$
	-0.73*	0.25*	0.37*	0.49*	0.61*	4.43*	3.54*	3.44*	-0.37*	-0.42*	-0.10
	(0.011)	(0.004)	(0.004)	(0.005)	(0.006)	(0.174)	(0.149)	(0.460)	(0.014)	(0.012)	(0.012)
Frequency Counts for the Ordered Response Categories											
Category	1	2	3	4	5	6					
Count	72,353	4,534	1,651	1,507	1,258	4,963					
			$\ln(L)$	=	-57,015.0 <sup>a</sup>						
			$\ln(L_r)$	=	-57,023.5 <sup>b</sup>						

\*Denotes the  $p$ -value  $< 0.001$  using the Wald  $\chi^2$ -test.

<sup>a</sup>Log-likelihood for the unrestricted model.

<sup>b</sup>Log-likelihood for the model under the restriction  $\beta_1 = \beta_2$ .

**Table 6**  
**Summary Statistics on the Order Type Chosen**  
**by 21 Institutional Traders from January 1991-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
<i>A: Buyer-initiated Trades</i>							
Limit Orders	653	98.52	2.71	2.81	12.4	1.3	0.0
Crossing Networks	523	7.71	1.85	1.34	0.1%	0.4%	0.0%
Working Orders	3,211	34.87	2.46	0.38	11.3	1.1	11.2
Market Orders	31,502	37.66	2.03	1.10	76.2	97.2	88.8
<i>B: Seller-initiated Trades</i>							
Limit Orders	672	88.40	2.65	2.65	10.1	2.2	0.0
Crossing Networks	113	20.41	1.68	0.84	0.1%	0.2%	0.0%
Working Orders	2,919	33.07	2.43	0.52	12.2	1.2	11.1
Market Orders	21,086	55.86	2.00	2.05	77.6	96.4	88.9

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 1 if order  $i$  results in the  $j^{\text{th}}$  order type category ( $j = 1, \dots, 4$ ),  $\alpha_j$  is an unknown partition,  $\beta$  is a vector of unknown coefficients,  $x_i$  is a vector of independent variables, and  $\Phi$  is the cumulative normal distribution. The order type categories are limit orders ( $j = 1$ ), crossing networks ( $j = 2$ ), working orders ( $j = 3$ ), and market orders ( $j = 4$ ). The linear combination  $\beta'x_i$  is given by:

$$\beta'x_i = \beta_1 Q_i^b + \beta_2 Q_i^s + \beta_3 MCap_i + \beta_4 D_i^{index} + \beta_5 D_i^{tech} + \beta_6 D_i^{OTC} + \beta_7 R_i$$

where  $Q_i^b$  ( $Q_i^s$ ) is the ratio desired order size to shares outstanding for buyer-initiated (seller-initiated) trades ( $\times 10^{-3}$ ),  $MCap_i$  is the market capitalization of stock  $i$  (in \$bill),  $D_i^{index}$  is an investment style dummy variable which equals 1 if the trading institution is an index fund and zero otherwise,  $D_i^{tech}$  is an investment style dummy variable which equals 1 if the institution bases their trades in part on prior price movements and 0 otherwise,  $D_i^{OTC}$  is a dummy variable taking the value 1 if the stock is traded over-the-counter and 0 otherwise, and  $R_i$  is the absolute value of the return for the traded stock over the 10 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.

	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	$\beta_6$	$\beta_7$
	-0.93*	0.14*	0.59*	-5.90	0.22	4.63*	0.22*	1.28*	0.05*	0.26
	(0.01)	(0.00)	(0.01)	(2.67)	(2.61)	(0.56)	(0.01)	(0.01)	(0.01)	(0.11)

Frequency Counts for the Ordered Response Categories			
Category	1	2	3
Count	6,089	1,592	7,000
			66,203

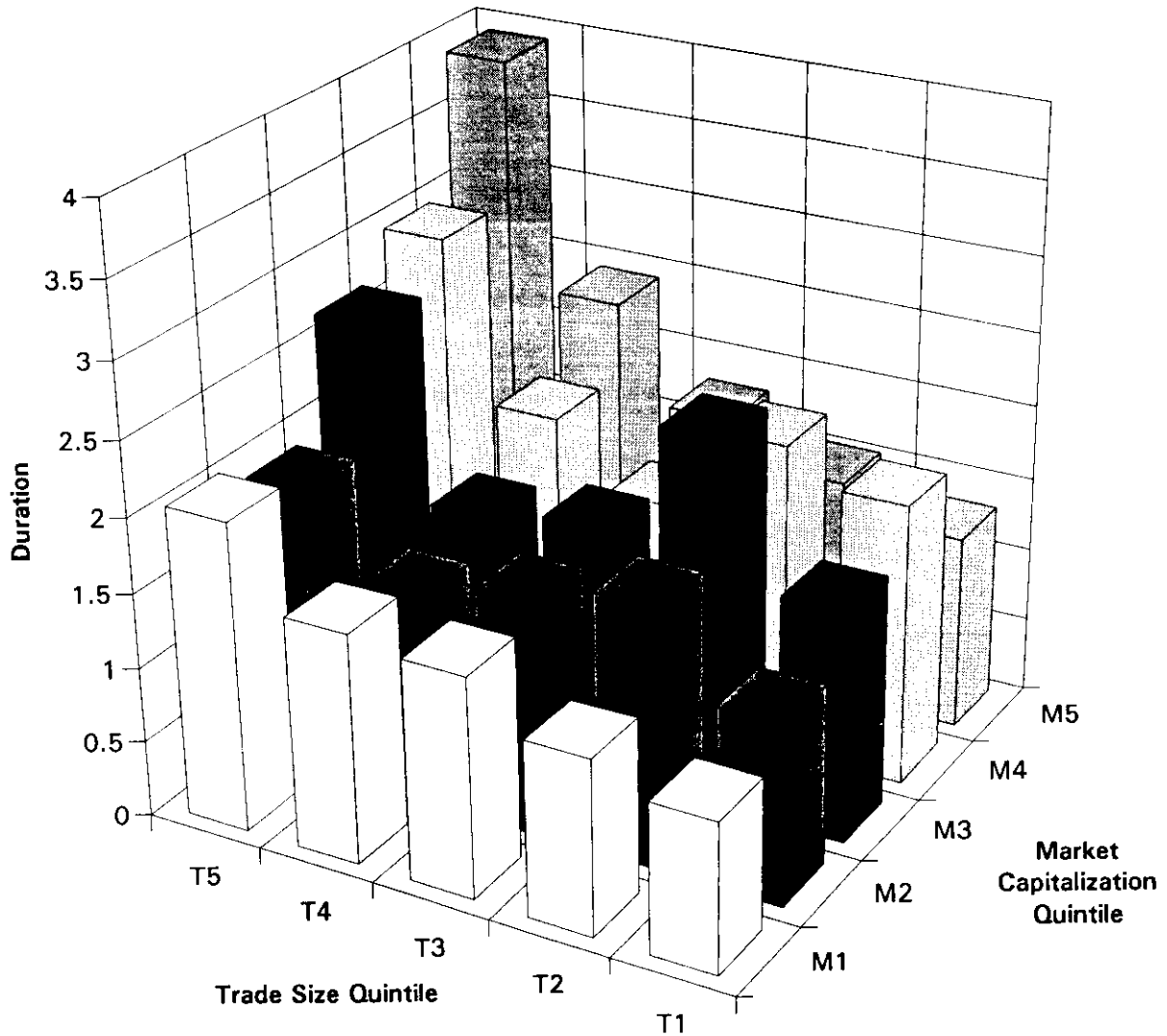
  

$\ln(L)$	=	-46,824.45 <sup>a</sup>
$\ln(L_r)$	=	-46,825.97 <sup>b</sup>

\*Denotes the  $p$ -value < 0.001 using the Wald  $\chi^2$ -test.

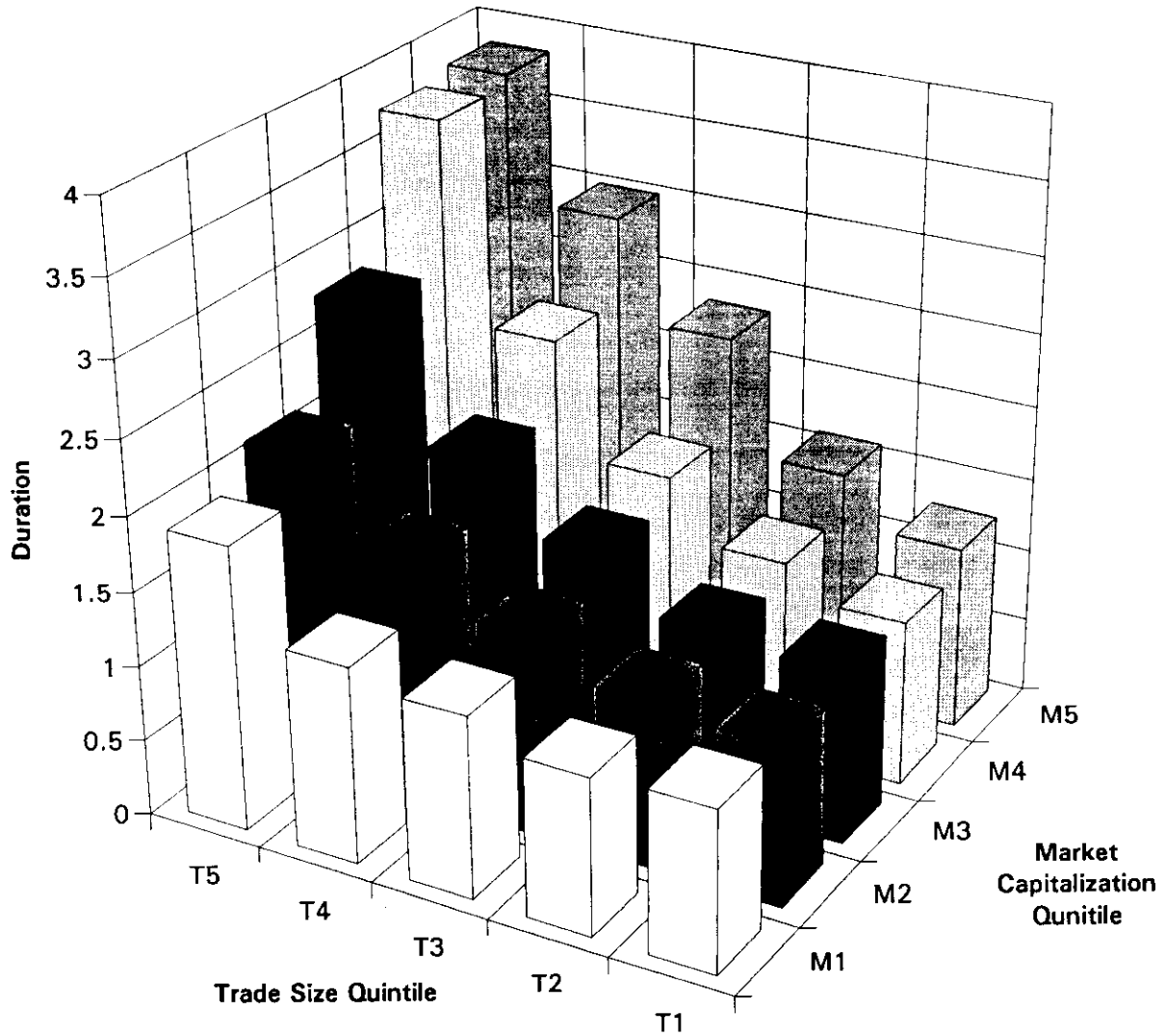
<sup>a</sup>Log-likelihood for the unrestricted model.

<sup>b</sup>Log-likelihood for the model where  $\beta_1 = \beta_2$ .



**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.



**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.

**ANATOMY OF THE TRADING PROCESS:  
EMPIRICAL EVIDENCE ON THE BEHAVIOR OF  
INSTITUTIONAL TRADERS**

by

**Donald B. Keim  
Ananth Madhavan**

18-93

**RODNEY L. WHITE CENTER FOR FINANCIAL RESEARCH  
The Wharton School  
University of Pennsylvania  
Philadelphia, PA 19104-6367**

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# Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders

Donald B. Keim  
and  
Ananth Madhavan\*

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# Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders

## **Abstract**

This paper examines empirically the behavior of institutional traders using unique data on the equity transactions of 21 institutions of differing investment styles during 1991-1993. The data provide a detailed account of the anatomy of the trading process, and include information on the number of days needed to fill an order and types of order placement strategies employed. We analyze the determinants of trade duration and the decisions regarding order type. Our analysis provides some support for the predictions made by theoretical models, but suggests that these models fail to capture important dimensions of trading behavior.



# 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.<sup>1</sup> A number of recent studies (Chan and Lakonishok (1993a, 1993b) and Keim and Madhavan (1992)) have focused on the price movements associated with institutional trades.<sup>2</sup> However, despite their importance in trading volume, relatively little is known about the actual trading behavior of institutional investors.

There are several reasons to focus on the trading behavior of this important group of equity market participants. Institutional traders, if faced with potentially very large position changes, may spread their trades over several days, and their continued presence on one side of the market may have an important effect on asset price dynamics. Further, if institutional traders initiate changes in their portfolio positions following abnormal price movements, their collective actions may stabilize prices if they follow contrarian strategies or exacerbate stock volatility if they do the opposite. Second, institutions' choice of order type may have important effects on market liquidity and execution costs. To the extent institutions rely on active strategies based on market orders, they act as demanders of liquidity. By contrast, if they rely on passive 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 rational trading behavior remain largely untested. As 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.

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<sup>1</sup>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 73.3% of the value of trading on the London Stock Exchange, and 76.6% of share volume on the Tokyo Stock Exchange.

<sup>2</sup>See also the Securities and Exchange Commission (1971) for one of the first studies of institutional trading. In addition, there is a large literature on the price impacts of large-block trades, some, perhaps most, of which were initiated by institutions. See, among others, Kraus and Stoll (1972), Scholes (1972), and Holthausen, Leftwich, and Mayers (1987, 1990).

Fourth, the data identify the trade as buyer- or seller-initiated. In most available databases, and therefore most of the research in this area, volumes are not signed and the trade initiation must be inferred indirectly using time-stamped quotation data. There are several recent exceptions. Keim and Madhavan (1992) examine institutional trades of large blocks of stock using data that not only permits identification of whether the trade was a buy or sell, but also who initiated the trade. Chan and Lakonishok (1993b) also examine the transactions of institutional investors and can ascertain whether a trade was a buy or sell. However, the information in their data does not permit identification of 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.

Finally, our data set is large; we have information on over 62,000 recent institutional orders (which usually are broken up) with a total value of over \$83 billion. Further, a wide variety of institutions are represented in the sample, and we have information on their investment styles (e.g., indexers, value managers, technical analysts). The data permit tests of detailed hypotheses regarding the 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. Our results do not suggest a consistent relation between past returns and the buy-sell decision, even for those institutions identifying themselves as technical traders. Rather, for the institutions in our sample, trade appears to be motivated by exogenous factors which seem to outweigh any association with prior returns. We then examine the process by which the desired demands are translated into executed trades. As predicted by most theoretical models, larger order quantities are associated with longer trading durations. However, the duration of trading increases with market capitalization, holding constant order size. Overall, though, the duration of trading is surprisingly short, indicating a high demand for immediacy. Finally, we find that buys take longer to execute than equivalent-sized sells, which is consistent with a larger price impact for buys versus

to past returns.

Position adjustments may 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, an institution’s trades may be determined primarily by its objectives or trading style. 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.

Other traders use technical trading strategies which 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 or future performance is of some importance, since positive feedback strategies exacerbate short-run price volatility while negative feedback strategies have the opposite effect. We can investigate this issue because our data indicate that actual date of the decision to trade as well as the dates of the individual transactions corresponding to the order.

#### *Trade Duration and Order Breakup*

In most dynamic microstructure models (e.g., Kyle (1985), Foster and Vishwanathan (1990), and 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 can reduce the overall price impact of a large order by breaking it up into several smaller trades.

Microstructure models (e.g., Kyle (1985)) also implicitly predict that the benefits

Before turning to the analysis of these hypotheses, we first describe the data.

### 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 the equity transactions of 21 institutions for various subperiods during the period January 1991 to March 1993. The institutions (which are identified to us only by number to preserve confidentiality) include investment managers, indexers, and pension funds, and differ in their motivations for trade, their trading styles, and the stocks traded. The structure of the data proves important in our subsequent empirical work, and accordingly we discuss this in some detail. Among other items, the data contain the following information that we use in our analysis of the transaction process:

- (i) the institution or manager initiating the trade;
- (ii) the date when the trading decision was made;
- (iii) the cusip number of the stock to be traded;
- (iv) the desired number of shares to be traded with a buy-sell indicator;
- (v) the closing price on the day before the decision to trade;
- (vi) the dates and number of desired shares corresponding to releases from the institution's trade desk to the brokers who will fill the trade;
- (vii) 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;
- (viii) 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);
- (ix) several additional fields that identify the average daily volume of transactions in the security, the market capitalization of the security, and an indicator for whether the stock was listed on an exchange or traded over-the-counter.

In addition, 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:

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-March 1993. In total, over \$83 billion of stocks were purchased or sold by the 21 institutions over the 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 to 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 \$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 slightly more skewed toward transactions in larger stocks.

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

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.

some bearing on theoretical models where it is common to assume traders adopt a decision rule specifying the order size as a function of the current price. In practice, however, institutional traders first decide on 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.<sup>6</sup> Specifying a trade quantity, as opposed to a trading rule, may be consistent with the presence of fixed order submission costs or the lack of feasibility of communicating a complicated dynamic trading strategy to the trading desk. Since this assumption affects trader behavior and hence transaction prices, it bears closer examination.

There is also discernable 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 may transpire 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, which allows us to investigate whether trades were motivated in part by past price movements. Table 3 presents, for buyer- and seller-initiated trades and the three categories of investment strategy, the value-weighted mean returns for one, two, four and eight weeks prior to the decision date. There is no evidence of a systematic relation between past price movements and the buy-sell decision, and the magnitude of the returns is small in relation to the standard errors. This conclusion appears to hold for a range of pre-trade horizons,

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<sup>6</sup>Under some circumstances, the decision is altered during the trading process. In general, however, this is relatively uncommon in our sample.

is 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 breakup and duration) increases with market liquidity.

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 figures 1 and 2, suggests that the period over which the order is executed (as well as trade breakup) is a function of order size, investment strategy, and market liquidity. From an econometric viewpoint, estimation of this function is complicated because 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 that takes 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,  $y_i^*$ , which is a linear function of a vector of underlying variables,  $y_i^* = \beta'x_i + \epsilon_i$ . The location of this response variable on the real line determines the duration of the trade. Given  $m$  distinct response categories, define  $m - 1$  constants  $\alpha_1 < \alpha_2 < \dots < \alpha_{m-1}$ . For notational convenience, we define  $\alpha_0 = -\infty$  and  $\alpha_m = +\infty$ . Order  $i$  falls in category  $j$  ( $j = 1, \dots, m$ ) if:

$$\alpha_{j-1} < y_i^* < \alpha_j. \quad (1)$$

We do not observe the underlying response  $y_i^*$  or the partitions  $\alpha_j$ , but we observe a variable  $y_{ij}$ , where  $y_{ij} = 1$  if  $y_i^*$  falls in category  $j$  and 0 otherwise. In this case, we set  $m = 6$ ; order  $i$  falls in category  $j$  if the duration was  $j$  and  $j \leq 5$ ; otherwise, the order falls in category 6.

From equation (1) we obtain:

$$\Pr[y_{ij} = 1|x_i] = \Pr[\alpha_{j-1} < \beta'x_i + \epsilon_i < \alpha_j|x_i], \quad (2)$$

index fund and zero otherwise,  $D_i^{tech}$  is an investment style dummy variable which equals 1 if the institution bases their trades in part on prior price movements and 0 otherwise, and  $D_i^{OTC}$  is a dummy variable taking the value 1 if the stock is traded over-the-counter and 0 otherwise.

Microstructure models predict that  $\beta_1$  and  $\beta_2$  are positive because larger orders result in longer durations. Similarly, the coefficient  $\beta_3$  on market capitalization is predicted to be negative since trades are executed more slowly in less liquid markets. The coefficients  $\beta_4$  and  $\beta_5$  capture the influence of the institution's trading style. Since indexers trade quickly using market orders to closely track a particular index, we expect  $\beta_4 < 0$ . Similarly, technical traders also tend to trade on relatively short-run market momentum, so that we expect  $\beta_5 < 0$ . The OTC 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),  $\beta_6 > 0$  because orders in over-the-counter stocks will be broken up more and will take longer to execute.

Table 5 presents the estimates of the 5 partition boundaries and 6 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. Both order-size variables are significant and the predicted positive relation holds. The difference in the magnitudes of the coefficients for the order-size variable for buys versus sells suggests that trade duration is longer, correcting for liquidity and style, for buys than for sells. To test the null hypothesis that equivalent buy and sell volumes have similar durations, we also estimated the model under the joint coefficient restriction  $\beta_1 = \beta_2$ . Define by  $L_r$  the value of the likelihood function evaluated under the restrictions imposed on the model. Then,  $\lambda = -2 \ln(\frac{L_r}{L})$  is distributed as a  $\chi_m^2$ , where  $m$  is the number of restrictions imposed. From Table 5,  $\lambda = 17$ , so that the null hypothesis that both buy and sell volumes have identical durations is rejected at below the 1% significance level.

This result provides new insights into previous empirical evidence suggesting an asym-



cause order size is being kept constant. This finding is contrary to the predictions of most microstructure models. Keim and Madhavan (1993) provide an explanation for why duration may (other things equal) increase with market liquidity. They develop a model of trading where order size, order type, and trade duration are endogenously determined. In their model, trade breakup (and hence duration) is positively related to order size. Further, the number of trades required to fill an order is determined in part by a trade off between price impact costs and order submission costs. Trade breakup 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 between these two cost components can result in a positive relation between breakup (or equivalently duration) and market capitalization. An alternative explanation is that it is more difficult to use passive strategies in thinly-traded stocks. As passive strategies take longer to execute, trade duration may increase with market capitalization. We show below that this explanation is not correct.

The trading style dummy variables in table 5 have significant negative coefficient estimates, as hypothesized. Finally, the coefficient on the OTC dummy,  $\beta_6$ , is negative, suggesting that trades in OTC stocks tend to have shorter durations than those of exchange listed stocks. As with the market capitalization variable, this finding may reflect higher order submission costs on the OTC market which offset the reductions in price impact from trade breakup. Alternatively, this result could reflect the relative difficulty of placing limit orders (or using crossing systems) in non-exchange listed stocks.

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. The results from these alternative specifications are very similar to those described above, and are not reported here.

We turn now to an analysis of the trader's choice of order type.

It is clear that there are marked preferences for various types of trading strategies. For example, liquidity-motivated traders like 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 that rapidly decays in value (e.g., technical traders) desire quick execution and tend to employ market orders. On the other hand, information traders with information that has a longer half-life (e.g., value traders) are more likely to trade slowly, using limit and working orders that are less costly. Finally, with the exception of crossing orders, passive order types tend to be adopted for larger trades.

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.<sup>11</sup> This property is particularly important for order type 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

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<sup>11</sup>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.

is no corresponding relation for seller-initiated trades.<sup>12</sup> This result is suggestive of a perception among institutional traders that buys are more difficult or costly to execute than equivalent sells, which is consistent with our results for trade duration.

The coefficient of market capitalization is positive suggesting that more active strategies are likely to be employed in more liquid markets. This is important because it indicates 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 indicates that orders for exchange-listed stocks are more likely to be executed using passive strategies, all other factors being equal. 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 OTC stocks is also consistent with the fact that trade duration is shorter in OTC stocks as reported in table 5. Finally, the market momentum coefficient is positive, as expected, and is significant at the one percent level. Active orders are more likely to be used in stocks where momentum is high.

## 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, 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. As

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<sup>12</sup>The coefficient  $\beta_1$  is negative and is significant at the 5% level, while the coefficient of  $\beta_2$  is not significantly different from zero. However, a likelihood ratio test indicates that the difference between the two coefficients is not significant.

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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 average value of the order; the average 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	Mean Dollar Value of Order (\$ thousands)	Mean 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 (%)
<i>A: Buyer-initiated Trades</i>						
Technical	1,609.6	50.5	2.47	1.50	0.033	94.93
Value	1,967.5	55.4	2.26	2.28	0.041	90.02
Index	207.2	6.3	1.52	1.93	0.002	100.00
Overall	1,150.3	34.8	2.08	1.80	0.011	95.92
<i>B: Seller-initiated Trades</i>						
Technical	1,690.0	54.5	2.13	1.43	0.027	96.11
Value	1,665.6	44.7	2.11	2.11	0.026	90.85
Index	885.8	23.8	1.55	1.62	0.015	99.93
Overall	1,598.1	48.4	2.06	1.65	0.025	94.99

**Table 4**  
**Summary Statistics by Duration-of-Trade Category**  
**for 21 Institutional Traders**

The table presents, for 6 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.

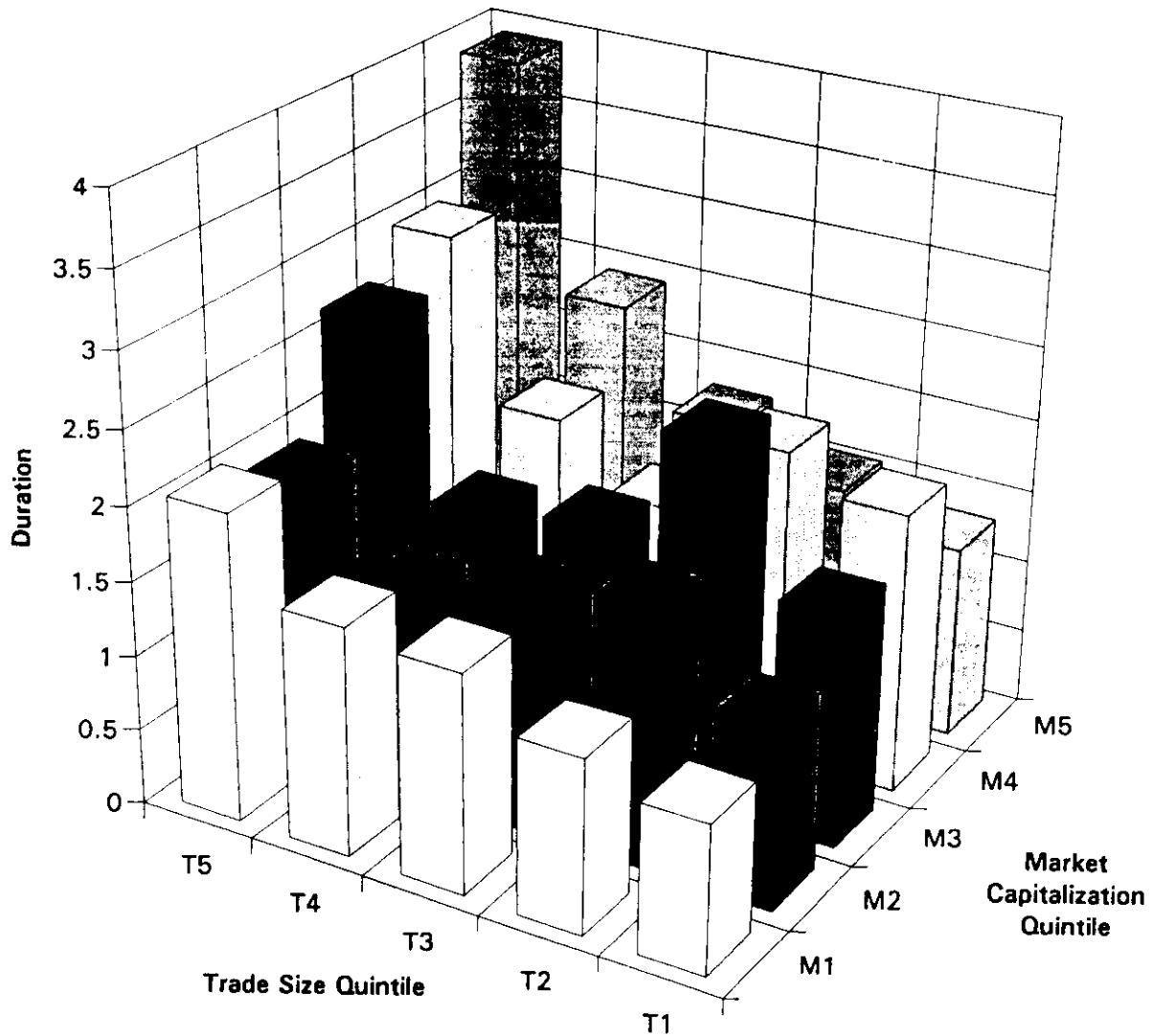
Duration (days)	Frequency	Order Size (thousands of shares)	Ratio of Order Size to Shares Outstanding	Market Capitalization (\$ billions)	Percentage of Total Trade Value by Investment Strategy			
					All Institutions	Value	Technical Index	
<i>A: Buyer-initiated Trades</i>								
1	30,421	30.074	0.009	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
<i>B: Seller-initiated Trades</i>								
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

**Table 6**  
**Summary Statistics on the Order Type Chosen**  
**by 21 Institutional Traders from January 1991-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
<i>A: Buyer-initiated Trades</i>							
Limit Orders	653	98.52	2.71	2.81	12.4	1.3	0.0
Crossing Networks	523	7.71	1.85	1.34	0.1%	0.4%	0.0%
Working Orders	3,211	34.87	2.46	0.38	11.3	1.1	11.2
Market Orders	31,502	37.66	2.03	1.10	76.2	97.2	88.8
<i>B: Seller-initiated Trades</i>							
Limit Orders	672	88.40	2.65	2.65	10.1	2.2	0.0
Crossing Networks	113	20.41	1.68	0.84	0.1%	0.2%	0.0%
Working Orders	2,919	33.07	2.43	0.52	12.2	1.2	11.1
Market Orders	21,086	55.86	2.00	2.05	77.6	96.4	88.9





**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.