Alternative Trading Systems*

Jennifer Conrad
Kenan-Flagler Business School
University of North Carolina at Chapel Hill
Chapel Hill, NC 27599
(919) 962-3132

Kevin M. Johnson
Aronson+Partners
230 South Broad Street, 20th Floor
Philadelphia, PA 19102
(215) 546-7500

Sunil Wahal
Goizueta Business School
1300 Clifton Road
Emory University
Atlanta, GA 30322-2710
(404) 727-8685
Email: Sunil_Wahal@bus.emory.edu

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Abstract

Using proprietary data, we examine institutional orders and trades filled by alternative electronic trading systems. Our data consist of almost 800,000 orders (corresponding to 2.15 million trades) worth approximately $1.6 trillion, between the first quarter of 1996 and the first quarter of 1998. These data allow us to distinguish between orders filled by external crossing systems, electronic communication networks (ECNs) and traditional brokers. We find that external crossing systems are used largely to execute orders in listed stocks, while ECNs concentrate in Nasdaq stocks. On average, broker-filled orders are larger, have longer duration, and higher fill rates than orders executed by alternative trading systems. Controlling for variation in order characteristics, difficulty, and endogeneity in the choice of trading venue, we find that realized execution costs are substantially lower on external crossing systems and ECNs. Our results shed light on the emergence of alternative electronic trading systems that provide significant competition for order flow, for both exchanges and dealer markets.

1. Introduction

The emergence of alternative electronic trading systems over the past decade has radically altered institutional trading practices. Such trading systems are frequently grouped into two categories: crossing systems (such as ITG's POSIT) in which institutional orders are brought together and "crossed" at some prevailing price, and electronic communication networks (ECNs), such as Instinet, that allow counterparties to trade anonymously at negotiated prices. These systems have experienced enormous growth and appear to provide a significant source of competition for order flow, for both exchanges and dealer markets. For instance, the nine currently operating ECNS account for almost 40 percent of the dollar volume of trading in Nasdaq securities (SEC, 2000).[1] Similarly, trading volume on POSIT, the most prominent crossing network, grew at a compounded annual growth rate of over 45 percent between 1988 and 1999, and recorded a total trading volume of 6.5 billion shares in 1999.[2]

The management of trading, and by extension the choice of trading venue, is an important issue for institutions. Institutional investors must, by law, seek "best execution" of their trades, and execution costs are an important determinant of investment performance. However, as Macey and O'Hara (1997) note, best execution is a multi-dimensional concept encompassing trade price, market impact, immediacy, timing, trade mechanism, anonymity, commissions and even quid-pro-quo arrangements. Alternative trading mechanisms offer different combinations of these aspects of execution quality and allow investors to pursue the tradeoffs between such attributes.

In addition to its obvious importance for practitioners, and for research in market microstructure, an understanding of alternative trading systems is also relevant from a regulatory perspective. A proliferation of such systems can cause fragmentation of

[1] The nine ECNs are: Archipelago, Attain, Instinet, Island, Bloomberg Tradebook, GFI Securities, Market XT, NexTrade, Redibook, and Strike.

[2] This competition is also evident in the response of exchanges and dealer markets to incursions by alternative trading systems, particularly in the realm of institutional trading. For instance, the NYSE recently introduced Institutional XPress, designed specifically to attract institutional order flow. Similarly, Nasdaq's SuperMontage seeks to compete for institutional orders by encapsulating features akin to those provided by ECNs, such as anonymous postings. See "Plan to upgrade Nasdaq trading passes the SEC," *Wall Street Journal*, 1/11/2001.

-system" which allows traders to anonymously enter orders on-screen and trade with other institutions, broker-dealers,

[3] Continued growth in such systems also prompted the adoption of Regulation ATS in 1998, requiring alternative trading systems to choose between being a market participant (e.g. broker) or registering as an exchange. To date, the vast majority of trading systems have chosen not to register as exchanges.

market makers and exchange specialists.[4] ECNs provide more immediacy than crossing systems in that they permit counterparties to anonymously negotiate, and therefore provide a price discovery mechanism. Finally, orders executed through the traditional brokerage system on the NYSE, Amex or Nasdaq are referred to as broker-filled orders. Broker-filled orders are the most aggressive in providing immediacy since brokers commit capital, and actively search for counterparties across all trading venues. This last category serves as the numeraire for our tests.

Our results suggest a large degree of exclusivity in the use of alternative trading systems - only 10 percent of all orders employ multiple trading mechanisms (i.e., 90 percent are single mechanism orders). The data also suggest important clientele effects. External crosses take place largely in listed securities whereas ECNs focus on Nasdaq stocks. This separation is natural, given the trading mechanisms employed by these systems. Since crossing systems provide no price discovery mechanism, they need at least two attributes to provide attractive fill rates. First, they need good primary-market price discovery to support the crossing system. The NYSE provides such a mechanism (see Hasbrouck (1995) for evidence). Second, they need a minimum threshold of trading volume by participants on the system so that the pool of liquidity is sufficiently large. ECNs, on the other hand, provide active price discovery – a feature that is particularly important when the primary market is relatively fragmented and has high bid-ask spreads. Therefore, Nasdaq stocks provide a natural setting in which ECNs can compete with market makers for order flow.

Our data also suggest important differences in the characteristics of orders across trading systems. For example, in dollar terms, the size of orders executed by crossing systems and ECNs are substantially lower than those executed by brokers. As a proportion of average trading volume, ECN-executed orders are comparable to broker-filled orders. In general, broker-filled orders are larger, are broken up into more trades and have higher fill rates than orders filled by alternative trading systems.

[4] During our sample period, all institutional trading on ECNs was conducted on Instinet. Other ECNs catering to institutional trading, such as Tradebook, did not commence operations until the 4th quarter of 1998.

To examine the competitive performance of alternative trading systems, we use the implementation shortfall method of Perold (1988) and Keim and Madhavan (1995, 1997). This method characterizes total execution costs as the sum of implicit (price-movement-related) and explicit (commission) execution costs. Given the differences in order and security characteristics across trading platforms, we use two methods of controlling for these characteristics in measuring differences in execution costs. First, we use a matched-sample approach that controls for trade direction (buy versus sell), order instruction, order size, exchange listing and market capitalization, but does not impose linearity or functional form restrictions. We find that external crosses have total execution costs that are substantially lower than those provided by traditional brokers. On average, the cost difference is approximately 0.30 percent, which for the average stock in our sample, corresponds to approximately 10 cents per share. The total execution cost difference between broker-filled and ECN-executed orders is higher, at 0.66 percent (23 cents per share). Most of these differences in execution costs are attributable to the prices at which trades are executed (implicit costs), rather than commissions (explicit costs).

The second method of controlling for differences in order characteristics employs a regression analysis. Regression-based measurement of execution cost differentials permits flexibility in controlling for other characteristics, and allows for institution-specific abilities in trading documented by Keim and Madhavan (1997). Using a regression specification that controls for security and order characteristics, and employs institution-specific fixed effects, the execution cost differential between external crosses and broker-filled orders is 0.15 percent for buys and 0.11 percent for sells. For ECN-executed orders, the differentials are 0.34 percent for buys and 0.55 percent for sells. These differences may be associated with a characteristic of order difficulty that we have not controlled for, or may be offset by a benefit that we cannot measure. We have examined a number of different specifications; our results are robust to those we have examined.

It is possible that the choice of trading mechanism is endogenous to (ex post) realized execution costs, particularly since each trading mechanism reflects a different level of effort on the part of the trader. We address the endogeneity issue by using an endogenous switching regression method described by Madhavan and Cheng (1997) to control for selectivity. The procedure involves estimating a first-stage probit regression predicting the choice of trading mechanism, which then feeds in to a second-stage execution cost regression. Using this method, however, does not change our basic conclusion; the cost differentials described above persist, and in some cases, widen. We also estimate the switching regressions using a matched sample of orders that ensures a common level of support across orders sent to competing trading platforms (see Heckman, Ichimura and Todd (1997)). Even with the matched sample, however, the cost differentials remain. Thus, orders that are sent to alternative trading systems are those that institutional investors perceive as being more likely to have higher execution costs when executed by brokers.

Finally, we focus our attention on orders where selectivity is likely to be largest, that is, orders that employ different trading mechanisms for constituent trades. Interestingly, we find that although brokers are the last method of execution in a majority of the orders, a substantial fraction (over 40%) of orders have their last trade executed on an alternative trading system. If the last portion of the trade is the most difficult, this suggests that the dealer market is not consistently the "market of last resort". We also conduct a trade-level analysis of such orders and again find that, controlling for both order and trade-level characteristics, execution costs are lower for crossing systems and ECN-executed trades.

The large and economically significant differences in order (and trade) characteristics, and in realized execution costs, could be due to at least two reasons. It is possible that alternative trading systems expand the opportunity set of execution services by providing combinations of execution-attributes unavailable through traditional trading mechanisms. In that sense, alternative trading systems can be thought of as completing the market for execution services. It is also possible that such trading systems simply provide cheaper execution for the *same* attributes, perhaps through the use of technology in lowering search and negotiation costs. For example, specific negotiation and reserve size features in ECNs may allow traders to manage the release of information in the trading process. It is important to note, however, that cheaper execution on alternative platforms may only be possible for certain types of order flow. That is, our results show differences in *realized* execution costs and are therefore conditional on execution. Regardless of the reason, the cost differentials suggest that electronic trading systems provide substantial competition for at least some types of order flow for organized exchanges, dealer markets and traditional modes of order execution.

Our paper is part of a small but growing literature that examines the impact of technology-based innovations in the trading environment. Hendershott and Mendelson (2000) develop a theoretical model to explore the consequences of the introduction of a crossing network on the underlying market. Other empirical papers examine the role of ECNs in price discovery. Huang (2000) uses quote data from the Nastraq database and concludes that ECNs are important contributors in price discovery. Barclay, Hendershott and McCormick (2001) examine ECN trades and find that average quoted, realized and effective spreads are smaller for ECN trades than for market makers (see also Barclay and Hendershott (2000) for an analysis of after-hours trading, some of which takes place on ECNs). In these studies, however, the analysis focuses on all trades occurring on a trading platform; the authors cannot distinguish between single mechanism and multiple mechanism trades, nor can they identify the sequence of the trade in the underlying order. In contrast, like us, Fong, Madhavan and Swan (2001) are able to identify the order from which trades are generated. They analyze data from the Australian Stock Exchange, which is itself electronic, and find that the magnitude of off-market trading (defined as the total of trading volume on ECNs, crossing systems and upstairs markets in Australia) is driven by institutional trading interest and liquidity. However, Fong, Madhavan and Swan (2001) do not analyze multiple mechanism orders and do not investigate sequencing in the use of trading platforms to fill such orders.

To our knowledge, this study represents the first comprehensive analysis of data on institutional investors' strategic use of multiple trading platforms in minimizing execution costs. There are, however, two related studies. Domowitz and Steil (1999) examine trading data from a single anonymous institution and compare execution costs across trading systems. Their data averages trade information across six month periods and they are forced to aggregate ECNs and crossing networks in their classifications. They find that electronic systems provide lower execution costs than market makers on Nasdaq, but cannot come to such a conclusion for listed securities. Naes and Odegaard (2001) also examine the trades of a single institution, the Norwegian Petroleum Fund. In a study of 4,200 orders that are first sent to crossing networks, and then to brokers, they find that execution costs of crossed trades are lower. They also present evidence that the cost of failing to execute on the crossing network can be significant.

Our paper proceeds as follows. In section 2, we provide some brief institutional details. Section 3 describes our data, and classification procedures. Section 4 presents the results and section 5 concludes.

2. Institutional details

In this section, we present a brief description of the rules and features of external crossing systems and ECNs used by institutional investors.

In external crossing systems, traders enter unpriced (buy or sell) trades, which are crossed at pre-specified times, at prices determined in the security's primary market. Since the trades are unpriced, such systems do not provide a direct price discovery mechanism. Moreover, immediacy is not guaranteed since crosses take place only at a few discrete points in time, and if there is an order imbalance, the trade may not be filled. After-hours crossing services to institutions are provided by three entities. First, the New York Stock Exchange's Crossing Session I crosses trades in individual stocks between 4:15 p.m. and 5:00 p.m. based on the NYSE closing price. Second, Instinet Crossing (not to be confused with Instinet's "day" ECN system) crosses listed stocks at the closing price on the NYSE, and Nasdaq stocks at the closing inside quote midpoint. Instinet Crossing is an after-hours cross with no preset time, but usually takes place between 7:00 p.m. and 8:00 p.m. Finally, the most prominent crossing network is ITG's POSIT. POSIT crosses trades seven times a day, at 9:45 a.m., 10:15 a.m., and hourly from 11:00 a.m. to 3:00 a.m. Each cross takes place at a randomly selected time within a five-minute window immediately following the scheduled time. The prevailing quote midpoint in the stock's primary market serves as the crossing price. Commissions on all three external crossing systems are usually fairly small, from one to two cents a share.

Unlike external crossing networks, ECNs allow traders to enter priced trades in a variety of forms in a screen-based system. The buyer and seller remain anonymous during the trading process and trade execution reports list the ECN as the contra-side party, thereby maintaining post-trade anonymity. Since trading on ECNs uses priced orders, such systems have the potential to contribute to price discovery over and above the stock's primary market. In fact, Huang (2000) finds that ECNs are important contributors to price discovery and are the dominant trading venue in eight of the ten most active stocks that he analyzes. Such systems afford traders a variety of features that provide considerable flexibility in managing execution costs. For instance, negotiation features permit users to conduct anonymous negotiations over price and size. Similarly, reserve size orders can be displayed such that only part of the available size is shown, facilitating the breakup of orders. As mentioned earlier, of the nine currently operating ECNs, Instinet is the only active one in our sample. The remaining commenced operations after the end of our sample period. Commissions on Instinet vary, and are usually determined by the amount of trading volume the institution contributes.

The traditional method of executing institutional trades is through the well-known broker system. For NYSE stocks, orders can be sent directly to the NYSE floor in which trades can be executed with or without specialist intermediation. Large orders can also be executed in the upstairs market, in which brokers search for liquidity and prices are determined by negotiation (see Hasbrouck, Sofianos, and Sosebee (1993), Keim and Madhavan (1996), and Madhavan and Cheng (1997)). For Nasdaq stocks, large institutional orders are typically handled by full service or dedicated brokers. These brokers find counterparties and negotiate a price to fill a trade, much like the NYSE upstairs market. Trading using traditional brokers is not anonymous and therefore can result in leakage of information. Commissions are negotiated, and like ECNs, depend on the volume generated by the institution.

3. Data

3.1 Data Sources

Our primary data are provided by the Plexus Group, a consulting firm to institutional investors that monitors the costs of institutional trading. The data record each unique order and the trades (transactions) resulting from that order. Order-level information is *ex ante* and includes the following: a ticker symbol, the market capitalization of the security, a buy-sell indicator that is based on the institution initiating the trade, the date when the trading decision was made, the closing price on the day before the decision date, the geometric mean of daily trading volume over the five days prior to the decision date, and an instruction variable indicating if the order is a market order, limit order or a cross. Each order can result in one or more trades. For each trade, the data show the number of shares bought or sold, the price at which the trade is executed, a broker ID indicating the broker responsible for executing the trade, and the commissions charged for the transaction (in cents per share). Institution names are removed from the database and replaced with institution codes to preserve confidentiality. Institution codes are mapped by Plexus into one of three investment styles (momentum, value and diversified). The data are similar in structure to those used by Keim and Madhavan (1995, 1997) and Conrad, Johnson and Wahal (2001) but represent a more recent and longer time series. Our sample comprises orders submitted by subscribing institutions from the first quarter of 1996 to the first quarter of 1998.

For a subset of tests, we also use volume data provided by Instinet Inc. Specifically, for a sample period matching with our Plexus data, Instinet provided us with the total number of shares traded on the Instinet "day" system for each security, on each calendar day.

3.2 Data Filters and Checks

We apply several filters to the raw data provided by the Plexus Group. We follow Keim and Madhavan and eliminate orders for stocks trading under $1.00. We also remove orders for which a currency identification variable provided by Plexus is not equal to two; this has the effect of removing orders in non-US stocks. Orders for which the broker instruction (i.e. market order, limit order or cross) field is either missing or equal to 'X' are also removed from the sample. This last filter has the effect of removing eight institutions from our sample, mostly from the latter part of the time series.[5] Although investment style information is missing for 14 institutions, we do not remove these from the sample since the remaining information on orders and trades is complete. Over time, new institutions enter the sample as they are added to Plexus's client base, and some existing institutions leave the database. We do not require a continuous presence for an institution to be in the sample.

These data filters result in a final sample of 797,068 orders, submitted by 59 unique institutions which generate approximately 2.15 million trades. Order-level data are matched with price and return information from CRSP. To ensure matching accuracy, ticker symbol information from Plexus is matched with ticker records on CRSP as of the decision date.

3.3 Classification Procedures

Based on data reporting protocols and guidance from the Plexus Group, we apply a classification algorithm that categorizes all trades into one of three categories. [6]

1. An *external cross* is identified if either one of the following four conditions are satisfied:
   (a) The broker ID is marked "POSIT", thus identifying the use of the POSIT crossing mechanism. The commissions for trades on POSIT are two cents per share.
   (b) The broker ID is marked "ITG" and the commissions are two cents per share. Early in the sample period, some institutions use ITG as the broker ID even though

[5] At the request of the Plexus Group, we also remove from the original sample one quarter of data for an institution for which data are suspect.
[6] An earlier version of this paper also reported information on a fourth category, internal crosses. Unfortunately, the accuracy of the data for this category are suspect and the results are no longer reported.

the trades are crossed on POSIT; this filter isolates such trades by eliminating trades done by ITG's full service brokerage operations.

(c) The broker ID is marked "CROSS", thus identifying the use of (after-hours) Instinet Crossing. The commissions for trades using Instinet's crossing operation are one cent a share.

(d) The broker ID is marked "Instinet" and commissions are exactly one cent per share.

2. All trades with a broker ID marked "Instinet" without commissions of one cent per share are regard as *ECN*-executed trades.
3. Trades not filled by the above three mechanisms are regarded as *broker-filled*.

Regulation ATS, adopted by the SEC in 1998, requires that organizations providing alternate trading systems (crossing services as well as ECNs) either register as an exchange or remain a broker-dealer. Since the majority of such organizations have chosen not to register as exchanges, they appear in our data as brokers.[7] As a result, the classification procedure described above relies on broker identification.

The classification algorithm also exploits regularities in commission schedules. For example, in 2 (b) above, when the broker ID is marked "ITG" we rely on commissions to isolate crossing (POSIT) trades and attribute the remainder to ITG's full service brokerage operations. We do not believe this results in a serious bias. Commissions on the trades marked "POSIT" are *always* two cents per share, suggesting that using commissions to classify trades marked "ITG" is appropriate. Moreover, only 10 percent of all ITG trades are thus attributed to full service brokerage. In the case of Instinet, commissions of one cent per share are similarly used to isolate crossing trades not directly marked as such (see 2 (d) above). This procedure influences only 5 percent of all trades in which Instinet (either "Instinet" or "Cross") is the marked broker ID.

Even given the above qualifications, it is possible that there is some mixing of trades across categories. For example, it is possible that some external crosses are classified as ECN trades or that some traditional brokerage trades are classified as ECN

[7] Only two such organizations have filed applications to register as exchanges (Island and NexTrade).

trades. Conversations with the Plexus Group indicate that the magnitude of such potential misclassification is quite small. Even if there is some degree of misclassification, such error would reduce (rather than increase) systematic variation in order characteristics and costs across the four categories.

4. Results

4.1 Descriptive Statistics

As noted earlier, each order can be filled by multiple trades, and while each *trade* can only fall into one of the three categories, an *order* can be filled by trades from multiple categories. Issues of execution quality are more appropriately addressed at the order, rather than the trade-level, so it is important to distinguish between orders executed using one or multiple mechanisms. If an order is filled entirely by trades executed in one of the three categories, we refer to it as a "single-mechanism" order; if more than one of the three categories are employed, we refer to it as a "multiple mechanism" order.

Table 1 shows the distribution of single and multiple mechanism orders. Of the total sample of 797,068 orders, approximately 91 percent (723,998) are single mechanism orders. These are unevenly distributed across the four categories; the majority (560,712 orders) are filled by traditional brokers, 112,159 orders by external crosses, and 51,127 by ECNs.

There appears to be considerable time series variation, but no trend, in the distribution of single mechanism orders. For external crosses, the number of orders per quarter generally ranges between 10,000 and 20,000. However, there are two notable exceptions. The third quarter of 1996 and the second quarter of 1997 contain only 2,817 and 1,948 such orders. This is because data for one institution (that is a frequent user of crossing services) are not available for these two quarters. The number of ECN-executed orders generally ranges between 4,000 and 6,000 per quarter.

The somewhat unstable sample sizes across the quarters (due to the addition and removal of institutions into the database by the Plexus Group) have two empirical consequences. First, we expect some instability in execution quality and costs over time that is simply due to sampling variation. As a result, in addition to providing pooled time-series results, we also present quarter-by-quarter estimates of execution costs. Second, it is possible that some effects observed in the data might be due to the idiosyncratic behavior of one particular institution. Therefore, we also control for institution-specific effects and abilities in estimating cost differences across the four categories.

4.2 Order Characteristics

We start our empirical analyses by providing some simple descriptive measures of single and multiple mechanism orders. Table 2 reports statistics on various measures of order size, order difficulty and security characteristics. We use two measures of order size: dollar order size (measured in thousands of dollars) and relative volume (defined as the number of shares traded, divided by the geometric mean of daily trading volume over the previous five days). Using both measures, the data show substantial differences in order size between the categories. The average size (in dollars) of orders sent to external crossing systems and ECNs are considerably lower than those worked by traditional brokers. For example, the average order sent to an external crossing system is for $187,000. The corresponding average for the ECN is $194,000 and for broker filled orders, is $1.4 million. For multiple mechanism orders, the average order size is also high ($2.0 million). While means are obviously skewed by particularly large orders, the same pattern is also evident in medians. Measured relative to average trading volume, however, we see that while broker-filled orders remain significantly larger than external crosses, they are comparable to ECN-executed orders.

In most models of information-based trading such as Kyle (1985), breaking up an order allows the trader to maximize his/her gains from information. From the perspective of minimizing execution costs, larger and/or more difficult orders are likely to be broken up so as to minimize the price impact of constituent trades (Bertsimas and Lo (1998)). The average number of trades in the external crosses and ECN categories are 1.29 and 1.53 respectively; for broker filled orders, this rises to 2.19 trades per order. For multiple mechanism orders (with the largest relative volume), on average 4.07 trades are required to fill the order. In fact, although multiple mechanism orders represent only 10 percent of the total number of orders, they represent 47.5 percent of dollar trading volume. Consequently, they are an important component of our sample in both type and volume.

Fill rates also vary. For external crosses, the fill rate is a function of liquidity on the system or prevailing counterparty depth, a factor that is exogenous to the trader. In contrast, traders using an ECN can negotiate anonymously and therefore endogenously increase the probability of a complete fill. Similarly, for orders filled by traditional brokers, prices can be negotiated, thereby increasing fill rates. Consistent with this, the percentage of complete fills is approximately 92 percent for external crossing systems but rises to 94 percent and 96 percent for ECN and broker-filled orders respectively. Multiple mechanism orders represent the most difficult of all categories, and have a complete fill rate of only 81 percent.[8]

The data also show clientele effects in which external crossing systems and ECNs compete for order flow in different dimensions. Extant studies document that transaction costs are lower on the NYSE than Nasdaq (see Bessembinder (1997, 1999), Huang and Stoll (1996), and Chan and Lakonishok (1997)) and that the NYSE provides the vast majority of price discovery for listed securities (see Hasbrouck (1995)). Since crossing systems do not provide price discovery, they compete for order flow by allowing traders to (passively) trade with each other. In other words, crossing systems require that the primary market provide adequate price discovery and that the system attracts a minimum threshold of volume from the primary market (Hendershott and Mendelson (2000)). The higher the primary market volume, the more likely the crossing system will attract order flow. Our results are consistent with these arguments. In our sample, over 90 percent of all orders executed on external crossing systems are for NYSE securities. These securities have an average market capitalization of $12.7 billion and an average trading volume over a five-day period prior to the submission of the order of 7.5 million shares.

[8] It is important to note that the 92 percent fill rate for external crossing systems is based on single-mechanism orders only. Inclusion of multiple mechanism orders clearly lowers fill rates.

In contrast, ECNs allow for active price discovery and can therefore compete with primary markets in which transaction costs are higher, and order flow is fragmented. High primary-market trading volume is not a prerequisite for ECNs since traders can negotiate prices. Consistent with this, almost 80 percent of all ECN-executed orders in our sample are for Nasdaq securities.[9] These stocks have a much lower market capitalization ($3.8 billion) and average trading volume (3.0 million shares) than for external crossing systems.[10]

4.3 Measurement of Execution Costs

We turn next to the execution cost of orders filled through these alternative systems. Given trade, order, and decision-level data, we follow well-established implementation shortfall methods for measuring execution costs. Specifically, following Perold (1988) and Keim and Madhavan (1997), we calculate order-level implicit and explicit trading costs as follows:

$$Implicit\,Cost = \frac{P_t}{P_d} - 1 \tag{1}$$

$$Explicit\,Cost = \frac{C_t}{P_d} \tag{2}$$

where P_t is the trade-volume-weighted average price at which the order is executed, P_d is the closing price on the day before the decision is made to purchase, and C_t is the volume weighted commissions per share. As Keim and Madhavan (1997) point out, since P_d represents an unperturbed price prior to the submission of the order, the implicit execution

[9] We verify that this concentration of ECN trading in Nasdaq securities is not isolated to our sample but is also evident in broader data. Using volume data on all securities provided by Instinet, we calculate Instinet's share of total trading volume in NYSE and Nasdaq securities for the securities in our sample. For NYSE securities, on average, Instinet accounts for 1.5 percent of trading volume. For Nasdaq securities, the corresponding figure is 31.2 percent. These effects are also evident in a multivariate framework. A simple regression of Instinet's market share on market capitalization and inverse price level has an adjusted R^2 of 6 percent. The addition of an exchange dummy variable increases the adjusted R^2 to 53 percent. The coefficient on this variable has a t-statistic of 663.

[10] It is interesting that there are also larger asymmetries between buy-sell ratios for external crossing systems and ECNs, than for broker-filled orders. The buy-sell ratio is 1.8 for external crosses and 2.1 for ECNs, compared with 1.0 for broker-filled orders. This may be because sells require more immediacy than buys, perhaps due to exogenous liquidity shocks.

cost represents the difference in performance between the returns to a paper portfolio versus a portfolio constructed from realized transaction prices.

Given the distribution of fill rates described earlier, it is important to adjust partially filled orders for opportunity costs (see Edwards and Wagner (1993). For the partially filled portion of an order, we compute opportunity costs as in equation one, but replace P_t with a closing price 10 days after the decision date (P_{+10}). This is tantamount to "closing the books" on the order at this time; the choice of the 10-day window corresponds to the 95th percentile in the distribution of the number of days required to fill an order. Total execution costs are simply the sum of the implicit and explicit costs defined above. For partially filled orders, the implicit cost is weighted by the fill rate and the opportunity cost is weighted by one minus the fill rate.

The costs described above are at the *order*-level. Thus they are different from trade (or transaction-level) costs traditionally computed from conventional market microstructure databases but similar to the trade-package costs reported by Chan and Lakonishok (1995, 1997), and the order-level costs presented in Keim and Madhavan (1995, 1997) and Conrad, Johnson and Wahal (2001). While these order level costs are appropriate descriptors for single mechanism orders, they present a problem for multiple mechanism orders because we cannot attribute an order-level cost to a particular trading mechanism. As a result, the majority of our analysis focuses on single mechanism orders. However, multiple mechanism orders provide a rich opportunity to examine the use of alternative trading mechanisms, holding order characteristics constant. Therefore, we return to an analysis of multiple mechanism orders in Section 4.8.

4.4 Univariate Order-Level Costs

Table 3 reports average order-level execution costs for all categories of single mechanism as well as multiple mechanism orders. Panel A shows implicit, explicit and total costs for the full sample. All costs are reported in percent, with standard errors in parentheses.

The data show large differences in execution costs across the categories. Multiple mechanism orders, evidently the most difficult to fill based on evidence in table 2, have the largest implicit costs (0.71 percent), followed by broker-filled orders (0.43 percent). The average implicit cost of external crosses is substantially smaller at 0.12 percent and the implicit cost of ECN-executed orders is 0.19 percent. Of course, this rank ordering of implicit costs is inversely related to the rank ordering for difficulty, as measured by order size. Given this, the pattern of execution cost differences is not surprising.[11]

In Panel B of Table 3, we show total execution costs for each quarter in the time series. The time-series variation in execution costs, and in execution cost differences, is large. For external crosses, the estimates vary from a low of 0.08 percent in the third quarter of 1997 to a high of 0.33 percent in the first quarter of 1998. The variation in costs for ECNs is even larger; the minimum is –0.08 percent and the maximum is 1.26 percent. This time-series variability in execution costs is largely due to sampling variation. As shown in table 1, the number of orders in each category varies considerably across quarters. As a result, the execution costs are estimated with less precision in some quarters than others. In general, however, across quarters, multiple mechanism orders have the largest execution costs.

4.5 Matched Sample Execution Cost Comparisons

4.5.1 Procedures and Results

Univariate comparisons of execution costs can be misleading. The trading mechanisms represent varying degrees of aggressiveness on the part of the institution. External crosses are the most passive since orders are exposed only to a fixed liquidity pool. ECN-executions are still more aggressive in that they allow for negotiations on price and quantity. The most aggressive is the use of traditional brokers who are willing to commit capital in the search for best execution. These differences result in a natural

[11] There also appears to be some variation in explicit costs, although the differences are much smaller. Explicit costs are smallest for external crosses and largest for ECNs, but this is at least partially true by construction since the classification algorithm described in section 3.5 relies on regularities in commission schedules.

sorting of order difficulty across the categories, and are evident in the results in Table 4. Therefore, any comparison of execution costs must, at the minimum, account for variation in order difficulty. In addition, there can also be substantial differences in the characteristics of the securities traded, which can influence liquidity and hence trading costs. In this section, we employ a matched sample methodology to control for order and security characteristics. In the following section, we employ a regression-based approach to the same problem.

Our matching procedure is straightforward. We match each externally crossed and ECN-executed order with broker-filled orders on the following dimensions: exchange listing (NYSE/Amex versus Nasdaq), buy or sell, relative volume and market capitalization. We also match on order instruction (market or limit) for ECN-executed orders. The first three matching criteria require exact matches but for the last two, we enforce a 10 percent tolerance (i.e., the market capitalization and relative volume of broker-filled orders have to be between 90 and 110 percent of the ECN or externally crossed order). This procedure allows us to match 99 percent of externally crossed orders and 90 percent of ECN executed orders. Once the matching is complete, we compute implicit, explicit and total execution cost differentials as the execution cost difference between the primary order and the matched broker-filled orders. If more than one broker-filled order fulfils the matching criteria, the average execution cost of the broker-filled (matched) orders is subtracted.

Table 4 shows average matched sample execution cost differentials, with standard errors in parentheses. The cost differentials for external crosses are large, statistically significant and robust across sample periods. The average implicit cost difference for the entire sample is –0.19 percent, while the average explicit cost difference is –0.11 percent, resulting in a total cost difference of -0.30 percent. Although there is quarterly variation in total costs differentials, most of this variation comes from implicit costs; explicit cost differences remain relatively flat at 9 to 11 basis points. Despite the time series variation, however, the cost of executing comparable orders on external crossing systems is significantly lower in every quarter.

Execution cost differences between ECN-executed orders and broker-filled orders are larger than those of external crossing systems. Over the entire sample period, the average implicit execution cost of ECN-executed orders is lower by 0.70 percent, with a standard error of 0.03 percent. Across quarters, the implicit cost differences are large and negative (ranging from –0.52 percent to –1.06 percent), with one exception. That exception is the third quarter of 1997, in which the implicit cost differential is positive (0.11 percent), but statistically insignificant (the standard error is 0.08 percent).[12] Even though the explicit costs are marginally positive (0.04 percent on average), the total cost differential across all quarters is –0.66 percent.

4.5.2 Matching Issues and Robustness

The matched sample methodology employed above has a number of obvious advantages. It does not presume linearity or any particular functional form in the relationship between order characteristics and execution costs, and provides intuitive estimates of cost differences. However, the estimates are only as good as the matching criteria and precision of the matches. For example, it is possible that the execution cost differentials that we document above are simply due to differences in average price levels between orders executed in the four categories. Since execution costs are computed as percentages (of P_d), a large percentage of low price stocks in a category could result in substantially higher execution costs – entirely unrelated to the mechanism's ability to provide low cost execution. To determine if this is the case, we compute the difference between the price of each order executed on an alternative trading system and the price of matching orders. The average price (percentage price) differences for externally-crossed and ECN-executed orders (from matched broker-filled orders) are \$1.22 (4.1 percent) and \$0.30 (2.1 percent), respectively. These differences seem unlikely to be large enough to account for observed differences in execution costs.

[12] This is also the quarter with the highest univariate execution cost for ECN-executed orders. This particular quarter coincides with the move to sixteenths in July 1997, as well as a change in the manner in which reserve order size was displayed on Instinet. Conversations with officials at Instinet suggest that this period of high execution costs may be a result of traders learning the new features of the trading mechanism.

The matching criteria employed above do not require that matched broker-filled orders be executed in the same quarter as the "primary" order. This provides considerable flexibility and allows for multiple matches. In fact, the median number of broker filled orders that match externally-crossed and ECN-executed orders are 166 and 57 respectively. However, given the quarter-to-quarter variation in sample sizes and order characteristics, it is possible that quarter-specific idiosyncratic effects account for observed execution cost differences. To determine if this is the case, we redo the matching with an additional criterion: we require that broker-filled orders execute in the same quarter. This reduces the median number of matches to 17 for externally-crossed orders and 8 for ECN-executed orders. The more restrictive matching criteria changes the execution cost differentials but does not change the overall inferences. For the full sample, the total execution cost difference between externally-crossed and broker-filled orders rises changes only marginally, from –0.30 percent to –0.31 percent and for ECN-executed orders, the differential goes from –0.66 percent to –0.59 percent.[13]

4.6 Regression-based Evidence

An alternative method for estimating execution cost differentials is to employ a regression-based approach; cross-sectional regressions of total execution costs on various control variables and indicator variables for the categories of interest could also provide estimates of execution cost differentials. A particular advantage of this approach over the matched sample technique is that it allows us to control for institution-specific effects, which we know from the evidence in tables 1 and 3 could influence the results.

Following Chan and Lakonishok (1995) and Keim and Madhavan (1997) we use independent (control) variables that capture well-known determinants of execution costs. Relative volume controls for the fact that orders that are large relative to normal trading volume are likely to have higher execution costs because of adverse selection effects. The

[13] We also implement an even tighter matching algorithm that provides better *ceteris paribus* comparisons. Specifically, we match each crossed or ECN-executed order with broker-filled orders in the same stock and in the same week. Unfortunately, we are only able to match 50 (30) percent of the crossed (ECN-executed) orders and the median number of matches is one. Nonetheless, for this small subsample, the average cost differential is –0.09 percent for external crosses and –0.06 percent for ECN-executed orders.

inverse of stock price accounts for price discreteness and the logarithm of market capitalization takes into consideration the fact that liquidity is typically greater for larger firms. An exchange indicator (equal to one for NYSE/Amex firms and zero otherwise) is included because of existing evidence that transaction costs are typically higher on Nasdaq. The volatility of returns (measured as the standard deviation of daily returns over a 10 day period prior to the decision date) and the cumulative size-decile adjusted return (measured over the same interval) are also included in the regression to reflect market conditions and because traditional trading mechanisms may be the liquidity provider of last resort. Finally, in some specifications, we include institution-specific indicator variables (fixed-effects) that capture institution-specific abilities in trading. Our primary variables of interest are indicator variables for external crosses and ECN-executed orders. We do not include an indicator variable for broker-filled orders to avoid perfect collinearity; such orders are captured by the intercept.

Table 5 presents separate regressions for buyer- and seller-initiated orders. The first regression presents base estimates while the second (which includes institution-specific indicator variables) presents more conservative estimates. Focusing on the base regressions, the coefficients on external crosses and ECN indicator variables are negative for both buy and sell orders. For buys (sells), external crosses provide execution costs that are 0.30 (0.31) percent lower than broker-filled orders. Similarly, ECN-executed buys (sells) are cheaper by 0.49 (0.79) percent. These estimates are similar in magnitude to those produced by the matched sample procedure. Inclusion of institution-specific fixed effects significantly lowers execution cost differentials. For buys (sells), the differences between externally-crossed and broker-filled orders falls to 0.15 (0.11) percent. Similarly, for ECN-executed buy (sell) orders, the cost differentials fall to 0.34 (0.55) percent. While these estimates are lower, the cost differentials remain economically meaningful.[14]

The regressions in table 5 pool the entire time series and therefore may miss substantial quarterly variation in the estimates. This is clearly a concern given the

[14] We also examine a specification in which the value-weighted market return (cumulated over the duration of the individual order) is included as a control variable. The execution cost differentials for both ECNs and crossing networks remain negative and of similar magnitude.

sampling variation evident in Table 1. Therefore, we also estimate regressions on a quarter by quarter basis, with and without institution-specific indicator variables. The intercept (for broker-filled orders), and coefficients on external cross and ECN-executed indicator variables for these regressions are provided in table 6. Panel A (B) presents coefficients from regressions without (with) institution-specific indicator variables. Across both panels, all but two (out of 36) coefficients on externally crossed orders are negative; as before, the two outliers correspond to the third quarter of 1997. The average of these coefficients is of a similar order of magnitude to those shown in table 5. Similarly, all but three (out of 36) coefficients on ECN-executed orders are negative.

4.7 Endogeneity Issues

The matched sample and regression-based approaches may adequately capture differences in order characteristics and difficulty, but still miss an important economic component of the differences between the trading mechanisms. As mentioned earlier, these mechanisms differ in how aggressively the trade is marketed. The more aggressive the trading mechanism, the more likely the order is to be filled. Thus, aggressive trading mechanisms are more likely to attract difficult-to-fill orders. Of course, the more difficult the order, the higher the *ex post* execution costs. Since the tradeoffs are clear *ex ante*, these arguments suggest endogeneity in ex post execution costs. For example, observed execution costs for ECNs are conditional on the trader having chosen to route the trade to the ECN (based on expected costs). This implies that regressions of realized execution costs on order characteristics provide inconsistent estimates.

Madhavan and Cheng (1997) face a similar problem in analyzing executions in the upstairs versus downstairs market of the NYSE because traders endogenously choose between executing trades in the upstairs or downstairs market. They adapt and implement a simple two-stage econometric procedure that explicitly corrects for this self-selectivity. Since the econometrics of this procedure, known as endogenous switching regressions, are described in Madalla (1983, p. 283) and Madhavan and Cheng (1997, p. 194-195), we do not reproduce it in detail here. However, we provide some basic intuition for the model to help motivate our regression specifications. The procedure consists of estimation of the following two-equation system:

$$y_i = b\ X_i + g\ Z_i + e_i \tag{3}$$

$$Z_i^* = q\, W_i + u_i \tag{4}$$

where

$$Z_i = \begin{cases} 1\ if\ Z_i^* > 0 \\ 0\ \ otherwise \end{cases}$$

where y_i is the (total) execution cost of each order, X_i is a vector of variables controlling for order difficulty and characteristics (and includes a constant), W_i represents a vector of instruments, and Z_i is a binary variable equal to one if the order is executed on an alternative trading system (external crossing or ECN) and zero if the order is broker-filled. The procedure requires a first stage structural probit regression that predicts the choice of trading mechanism (as in equation (4)). The second stage regression (equation 3) then uses the estimates from the first stage regression to provide consistent estimates of â and ã.

To implement the procedure, we create two subsamples: one with external crosses and broker-filled orders, and another with ECN-executed orders and broker-filled orders. The regressions are then estimated separately for these subsamples. Like most solutions to endogeneity problems, the first stage regression requires good exogenous instruments (W_i) for the system to be identified and well specified. We identify factors that are important to the choice of trading venue. For alternative trading systems, we use an exchange indicator variable, three indicator variables for the investment style of the originating institution (momentum, diversified and value), and the volatility of return in the asset as instruments in the probit model.[15] The exchange indicator variable picks up clientele effects of the sort described in section 4.2, and is an important determinant of the trading mechanism used to execute an order. The investment style indicator variables account for the natural tendency

[15] As with the OLS regressions, we examined a specification in which the value-weighted market return, cumulated over the duration of the order, is included as a control variable in the first-stage regression. The empirical results were similar: the execution costs of both ECNs and crossing networks were lower, by approximately the same magnitude.

of institutions with aggressive investment styles to use aggressive trading mechanisms. For example, an institution following a momentum trading style may be less likely to use passive crossing systems because of a potentially lower likelihood of the order being filled. On the other hand, an institution with a value-based investment style, anticipating lower execution costs and being more patient, may be more likely to use passive crossing systems. Since we are missing style information for 14 institutions, the regression does not suffer from perfect collinearity. Finally, the volatility of return proxies for the potential benefit of considering different trading mechanisms.[16]

Panel A of Table 7 shows the results of the first stage regressions for the two subsamples, estimated separately for buys and sells. Since the magnitude of coefficients is not easily interpretable, we also report marginal effects (changes in probabilities) in square brackets. For indicator variables (exchange listing and investment style indicators), the change in implied probabilities are computed assuming a change in the independent variable from zero to one. For the continuous variable (the volatility of return), the change in probability is computed assuming a one standard deviation change from the mean of the variable.

The first stage regressions appear to be well specified. The psuedo-R^2's range from 0.13 to 0.22 and all of the variables have statistically significant coefficients. More importantly, some of the implied probabilities are quite large. For instance, for buys, an order in a listed stock is 12 percent more likely to be crossed and 23 percent less likely to

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[16] We are grateful to George Sofianos for suggesting the volatility variable. Another instrument we considered for the first stage probit regression is a measure of the liquidity pool available on the alternative trading system. For example, an institutional trader wishing to buy 100,000 shares of Cisco Systems would presumably think it important to know how much "depth" there is in Cisco Systems at an ECN, perhaps based on historical trading experiences. For the first stage of the ECN regressions, we obtained supplementary data from Instinet Inc. to compute such a variable. Specifically, we compute the geometric mean of trading volume in a security on the Instinet day system, over a five day period prior to the decision date. We then scale this by the geometric mean of total trading volume across all trading venues in the security, over the same five day period. This "Instinet volume" measure is essentially a market share that measures the liquidity pool available on Instinet, and could be systematically related to the decision to send an order to Instinet. However, our analysis showed that this proportional volume measure added relatively little to the explanatory power of our first stage ECN regression, perhaps because it is highly correlated with the exchange indicator. Consequently, we do not report regressions with this variable included. In addition, lack of similar data from external crossing systems prevents us from using a liquidity variable for the external crossing system regressions.

be executed on an ECN. Similarly, a one standard deviation increase in the volatility of return results in a large increase in the probability of choosing an ECN and a large decrease in the probability of choosing a crossing network.

Our primary interest, however, is in the second stage regressions. As in tables 5 and 6, these regressions (shown in panel B) use market capitalization, relative volume and inverse price as independent variables. Controlling for selectivity, the estimates imply that execution costs at ECNs are 0.62 percent lower than traditional brokers for buyer-initiated orders, and 0.67 percent lower for seller-initiated orders. For external crossing networks, buy (sell) orders have cost differentials of 0.56 percent (0.70 percent). Thus accounting for selectivity in the distribution of ex post execution costs provides estimates of cost differences that are similar in sign, and generally larger in magnitude compared to the matching and regression-based procedures employed earlier.

The inclusion of institution-specific variables in the second-stage regressions (not shown in the table) changes the results slightly: while the execution costs for ECNs buys and sells are lower (by 26 and 45 basis points, respectively), only crossing network buy orders are cheaper (by 18 basis points). Crossed sell orders are associated with an *increase* in costs of 27 basis points (although this cost is not statistically significant.)

Heckman, Ichimura and Todd (1997) analyze the sources of selection bias in a problem in which some sample elements receive a "treatment" while others do not. The analogous treatment in our sample is the choice of a particular alternative trading system. They show that the selection bias associated with differences in the characteristics (or support) of the sample elements is an important source of bias. Consequently, we also estimate the endogenous switching regression on matched samples of the orders, where the matching is identical to that used to construct Table 4. Although we do not report these results in the interest of brevity, the differentials in the execution costs of alternative trading systems, compared to broker-filled orders, continue to be negative. ECN buys (sells) have execution costs that are 0.71 (0.74) percent lower, and crossing network buys (sells) have execution costs that are 0.54 (0.65) percent lower. [17] Thus, these differentials are comparable to those reported in Table 7, and larger in three out of four cases than the differences in execution cost estimated using the OLS regression in Table 5. The fact that differentials widen in the majority of cases when we control for selection bias suggests that orders that are more likely to go to an alternative trading system have higher expected (broker-filled) execution costs even after controlling for other specific order characteristics. This result is similar to that of Madhavan and Cheng (1997), who find that liquidity-motivated orders are more likely to be directed to the upstairs market because their expected price impact in the downstairs market is higher.

4.8 Multiple Mechanism Orders: An Exploratory Analysis

4.8.1 The Use of Alternative Trading Mechanisms

Thus far, our analysis has focused on orders in which all trades are executed using a single trading mechanism. In this section, we shift our attention to multiple mechanism orders. Multiple mechanism orders are particularly interesting. By definition, order characteristics are held constant across the trades, and the investor chooses not only how to break up the order, but where to place the trades and in what sequence the trading venues will be used. As described earlier in Table 1, there are 73,070 such orders, representing approximately 10 percent of the entire sample and 47.5 percent of the dollar trading volume in our sample. The average order size is $2.0 million, significantly larger than single mechanism orders and on average, 4.07 trades are required to fill these orders.

We start by describing the use of the three trading mechanisms in filling these orders. We calculate the number of trades required to fill each order and then describe the frequency (percentage) with which each trading mechanism is used in filling that order. The results of this calculation are described in Table 8, with a separate percentage reported for each trade sequence (e.g. whether the trade was the 1st, 2nd or 3rd in filling a 3-trade

[17] With institution-specific indicator variables included in the matched sample second-stage regression, the differentials continue to be large and negative for ECNs (61 and 75 basis points for buys and sells, respectively), but are statistically insignificant for crossing networks (-4 and +9 basis points for buys and sells).

order). Naturally, the percentages for each n-trade order add up to 100. To conserve space, we only show results for orders that last less than or equal to 10 days.

The results provide some indication of the strategic use of the different trading systems. ECNs appear to be just as frequently used in the early part of the order as the later part of the order; the percentages across trade sequences are relatively flat. There is a small decline in the use of external crossing networks as the last trade in an order, and a corresponding increase in the use of broker-filled orders. For example, for 4-trade orders, the use of external crossing systems drops from 7.1 percent for the 3rd trade to 5.2 percent for the last (4th) trade. Not surprisingly, since the percentages must add up to 100, the use of broker-filled orders (correspondingly) increases from 12.2 percent to 14.4 percent.

If there is any urgency or additional difficulty in completing an order, as there may be for the last trade in an order, an external crossing network may not be used since it is a passive provider of liquidity. Urgency requires a search mechanism, and both ECNs as well as traditional brokers provide such a search mechanism. To the extent that the search for counterparties on an ECN is restricted to participating institutions, however, the risk of not filling the trade may be larger. This suggests that traditional brokers may be used to fill trades where the opportunity cost of not filling a trade is large. Indeed, such selectivity can also be characterized by describing the sequences with which different trading mechanisms are used to fill trades in an order. To do this, for each order, we collapse adjacent trades executed under the same trading mechanism (i.e. two adjacent trades filled by an ECN would be regarded as one) and then calculate the number of unique sequences represented in the data. For example, if a two-trade order in which the first trade is filled by an ECN and the second by a broker would be represented by the symbols “EB”. Similarly, if the first trade were filled by a crossing system and the second trade were filled by a broker, the order would be represented by the symbol “XB”.

There are approximately 1,100 unique sequences represented in the 73,070 multiple mechanism orders; 95 percent of all orders involve less then 5 switches between trading mechanisms. There is some evidence that brokers tend to be last in completing an order -- approximately 60 percent of the sequences end with “B” (i.e. the last trade is filled by a broker). This is partially consistent with the conjecture in Hendershott and Mendelson (2000) that the dealer market may become the "market of last resort." It is important to note, however, that the frequency in the use of alternative trading systems for the last trade (at around 40%) drops off only slightly, and is well above zero.

We wish to compare the execution costs of broker-filled and alternative trading system trades. However, calculating execution costs at the trade level is complicated by the strategic decisions of investors, who are presumably concerned with minimizing the execution cost of the *order*. Moreover, given the clustering in the sequences, with brokers more frequently trading the last piece of the order, trade-level execution costs need to control for the position of the trade in the sequence, as well as order and trade difficulty. The complexity of the decision process, as seen in the number of sequences in our data, inevitably makes these controls imperfect. With this caveat in mind, we proceed to an examination of trade-level execution costs for multiple mechanism orders.

4.8.2 Trade-level Execution Costs

We compute execution costs for each trade as in equations (1) and (2), but set the numerator in both equations to equal the trade price and commissions of the single trade, rather than a value-weighted average of all trade prices and commissions comprising the order. Therefore, for implicit costs, P_d still represents the unperturbed benchmark price.[18]

Using this measure of trade-level costs, we then estimate multivariate regressions similar to those in tables 5 and 6. Since the dependent variable is measured at the trade (and not order) level, in addition to the order-level control variables (market capitalization, order size, inverse price, return volatility, cumulative pre-order size-decile adjusted returns, and exchange indicator) used earlier, we use a number of trade-level controls. For instance, relative trade size, defined as the number of shares in the trade divided by the number of shares in the order, proxies for the information content and difficulty of the trade. In addition, two trade-level control variables capture the influence of earlier trades

[18] An alternative would be to measure implicit costs as deviations of trade prices from prevailing (or lagged) quote mid-points. However, since our data do not contain accurate time-stamps, we cannot match with conventional (intraday) sources of quote data.

from the order on market prices. Specifically, we use the trade sequence number (a number equal to the chronological sequence number of the trade in that order), and the cumulative lagged implicit cost (defined as the price movement from P_d to the execution price of the prior trade in that order). We also include the number of switches between trading mechanisms (as described earlier) and a dummy variable equal to one if the last trade in the order was executed by a broker since broker executions are the most aggressive of the three categories. As before, the regressions are estimated separately for buys and sells, and the results are reported in Table 9.

Our primary interest is in the indicator variables for whether the trade was executed using an external cross or an ECN. The coefficients for external crosses and ECN-executed trades are negative and statistically significant in both regressions. For external crosses, the coefficients are -0.08 for buys and -0.03 for sells. For ECN-executed trades, the corresponding cost differentials are –0.21 percent and -0.23 percent respectively.[19] The dummy variable which indicates that the last trade of the order was executed by a broker, has a positive coefficient which is both economically and statistically significant for buy orders, at 14 basis points. For sell orders, the differential is smaller (4 basis points) and statistically insignificant. Thus, there is some evidence, particularly for buy orders, that brokers handle the last, and most difficult, component of the order. Even allowing for this, however, the execution cost differences between trading systems that exist at the order-level for single mechanism orders also appear, albeit to a smaller extent, at the trade-level for multiple mechanism orders.

5. Conclusion

This paper examines the execution costs of trades sent to traditional and alternative trading systems. In a sample of $1.6 trillion in trades executed by 59 different institutions between the first quarter of 1996 and the first quarter of 1998, we find that there is substantial variation in the trading venues used by these institutions, and in the execution

[19] Since these execution costs are at the trade-level, the absolute value of the cost differentials will be smaller than for order-level regressions.

costs of these trades. We control for differences in order characteristics using both a matching technique and a regression analysis. We find that orders sent to traditional brokers have higher execution costs than those executed by alternative trading systems. External crossing systems that are passive trading systems with no price discovery function, have lower realized execution costs. ECN's, which aid in price discovery, have the lowest execution costs. We also control for endogeneity in the trading venue selection process by using an endogenous switching regression but the ordering of execution costs that we find above persists. In a sample of multiple mechanism orders, in which institutional investors make strategic use of different trading platforms to minimize execution costs, we continue to find that alternative trading systems execute trades at slightly lower costs.

Our results are important for practitioners interested in the best execution of their investment strategies, and for regulators and academics interested in the consequences of fragmentation. For the former, our results suggest that optimization of execution strategies should include the decision of where to execute trades in an order. For the latter, our results suggest that alternative trading systems provide significant competition to traditional trading mechanisms. Volume on crossing systems that provide no price discovery function has a natural upper bound since the system cannot exist independently of the primary price-setting mechanism, whether it be an exchange or dealer market. To the extent that other systems (such as ECNs) provide a price discovery mechanism, they can exist and grow independently.

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Table 1

Distribution of Order Types

This table shows the distribution of various types of orders. Single mechanism orders are those in which all the trades in an order are executed in one of the three categories listed below. Multiple mechanism orders are those in which more than one of the three trading mechanisms is used to fill the order. External crosses refer to orders executed on ITG Posit or Instinet's Crossing Network. Orders executed on Instinet's anonymous trading system are labeled ECN. Broker filled orders are those that are filled via traditional brokerage services.

	Single Mechanism Orders			Multiple Mechanism Orders
Quarter	External Cross	ECN	Broker Filled	
961	11,989	5,596	41,082	7,364
962	7,433	6,400	66,642	9,844
963	2,817	6,700	42,630	9,116
964	10,982	6,618	70,954	10,316
971	17,937	6,379	76,828	8,107
972	1,948	6,487	79,332	8,955
973	23,924	5,115	58,736	6,311
974	18,833	4,967	77,060	6,872
981	16,296	3,315	47,448	6,185
All	112,159	51,127	560,712	73,070

Table 2

Descriptive Statistics

This table shows characteristics of various types of orders. Single mechanism orders are those in which all the trades in an order are executed in one of the three categories listed below. Multiple mechanism orders are those in which more than one of the three trading mechanisms is used to fill the order. Average trading volume is the geometric mean of daily trading volume five days prior to the decision date. Relative volume is defined as the number of shares in the order divided by average volume. The fill rates are computed by calculating the percentage of the order that is filled.

	Single Mechanism Orders			Multiple Mechanism Orders
	External Cross	ECN	Broker Filled	
Order Size ($000)				
10th Percentile	6	9	8	70
Mean	187	194	1,474	2,005
Median	45	53	137	587
90th Percentile	821	360	2,821	4,768
Relative Volume	0.07	0.35	0.30	0.67
Number of Trades	1.29	1.53	2.19	4.07
Fill Rates				
% Partial Fill	7.87	5.90	3.94	16.24
% Complete Fills	92.13	94.10	96.06	83.76
# Buy Orders	71,268	34,371	286,908	40,922
# Sells Orders	40,891	16,756	273,804	32,148
NYSE/Amex	101,285	12,971	425,002	44,474
Nasdaq	10,874	38,156	135,710	28,596
Trading Volume	7,586	3,022	7,120	6,022
Market Value ($M)	12,787	3,803	11,122	9,239

Table 3

Univariate Execution Costs

This table presents implicit, explicit and total execution costs various types of orders. Single mechanism orders are those in which all the trades in an order are executed in one of the three categories listed below. Multiple mechanism orders are those in which more than one of the three trading mechanisms is used to fill the order. Implicit costs are defined as $(\frac{P_t}{P_d} - 1)$ where P_t is the volume-weighted average price at which the order is executed and P_d is the closing price on the day before the decision is made to purchase or sell the security. Explicit costs are calculated as commissions per share divided by P_d. For partially filled orders, opportunity costs are imputed by "closing the books" on the unfilled portion of the order with the closing price 10 days after the decision date. Total costs represent the sum of implicit, explicit and opportunity costs (if any).

	Single Mechanism Orders			Multiple Mechanism Orders
	External Cross	ECN	Broker Filled	
Panel A: Full Sample				
Implicit Costs	0.123	0.189	0.427	0.715
	(0.008)	(0.022)	(0.004)	(0.018)
Explicit Costs	0.065	0.186	0.163	0.124
	(0.001)	(0.001)	(0.001)	(0.001)
Total Costs	0.189	0.376	0.591	0.838
	(0.008)	(0.022)	(0.005)	(0.018)
Panel B: Total Costs by Subperiod				
961	0.200	0.293	0.564	0.64
	(0.023)	(0.067)	(0.017)	(0.052)
962	0.328	0.353	0.501	0.467
	(0.027)	(0.053)	(0.011)	(0.043)
963	0.120	-0.085	0.693	0.915
	(0.064)	(0.074)	(0.017)	(0.052)
964	0.130	0.268	0.590	0.722
	(0.025)	(0.068)	(0.012)	(0.048)
971	0.225	0.392	0.654	0.920
	(0.023)	(0.055)	(0.017)	(0.051)
972	0.268	0.296	0.592	0.934
	(0.066)	(0.061)	(0.012)	(0.060)
973	0.055	1.266	0.543	1.334
	(0.016)	(0.073)	(0.015)	(0.067)
974	0.173	0.224	0.619	0.857
	(0.021)	(0.069)	(0.013)	(0.067)
981	0.332	0.668	0.564	0.973
	(0.023)	(0.098)	(0.016)	(0.059)

Table 4

Matched Sample Execution Cost Differentials

Each order executed via external crosses or ECNs is matched with orders executed by brokers on the following dimensions: exchange listing (NYSE/Amex vs. Nasdaq), buy or sell, order instruction (market or limit order), relative volume (with a 10% tolerance) and market capitalization (with a 10% tolerance). Where more than one broker-executed order matches, the average execution cost of all matched (brokerage) orders is calculated. The table shows the average implicit, explicit and total execution cost differential between the matched sample and the orders of interest. Standard errors appear in parentheses.

	External Crosses			ECNs		
	Implicit	Explicit	Total	Implicit	Explicit	Total
961	-0.29	-0.09	-0.37	-0.94	0.06	-0.86
	(0.02)	(0.00)	(0.02)	(0.08)	(0.00)	(0.08)
962	-0.19	-0.09	-0.28	-0.76	0.04	-0.72
	(0.02)	(0.00)	(0.02)	(0.06)	(0.00)	(0.06)
963	-0.39	-0.07	-0.46	-1.06	0.06	-1.00
	(0.07)	(0.00)	(0.07)	(0.09)	(0.00)	(0.09)
964	-0.23	-0.09	-0.32	-0.93	0.05	-0.88
	(0.02)	(0.00)	(0.02)	(0.02)	(0.00)	(0.02)
971	-0.09	-0.10	-0.19	-0.52	0.03	-0.49
	(0.02)	(0.00)	(0.02)	(0.07)	(0.00)	(0.07)
972	-0.30	-0.08	-0.38	-0.65	0.03	-0.62
	(0.07)	(0.00)	(0.07)	(0.08)	(0.00)	(0.08)
973	-0.29	-0.11	-0.40	0.11	0.03	0.14
	(0.02)	(0.00)	(0.02)	(0.08)	(0.00)	(0.08)
974	-0.17	-0.10	-0.27	-0.82	0.01	-0.81
	(0.02)	(0.00)	(0.02)	(0.08)	(0.00)	(0.08)
981	-0.06	-0.11	-0.17	-0.60	0.04	-0.56
	(0.02)	(0.00)	(0.02)	(0.12)	(0.00)	(0.12)
Full	-0.19	-0.11	-0.30	-0.70	0.04	-0.66
Sample	(0.01)	(0.00)	(0.00)	(0.03)	(0.00)	(0.03)

Table 5

Total Execution Cost Regressions

This table presents estimates of cross-sectional regressions of total execution costs on the variables listed below. The independent variables include the logarithm of market value of equity, the logarithm of relative volume (the number of shares traded divided by the geometric mean of daily trading volume over the previous five days), the inverse of the stock price on the day prior to the trading decision, an exchange indicator variable equal to one if the stock is listed on the NYSE/Amex, zero otherwise, the standard deviation of daily returns from 10 days prior to the decision date, the cumulative size-adjusted return from 10 days prior to the decision date, and indicator variables for whether the order was executed via an external cross or on an ECN. Since there is no indicator variable for broker-filled orders, it is captured by the regression intercept. The sample consists of all single mechanism orders over all subperiods. P-values appear in parentheses.

	Buys		Sells	
Intercept	0.0099	0.0058	0.0199	0.0197
	(0.00)	(0.00)	(0.00)	(0.00)
Log (Market Cap)	-0.0003	-0.0007	-0.0001	-0.0007
	(0.00)	(0.00)	(0.00)	(0.00)
Log (Relative Volume)	0.0005	0.0007	0.0005	0.0006
	(0.00)	(0.00)	(0.00)	(0.00)
Inverse Price	0.0777	0.0854	0.0414	0.0505
	(0.00)	(0.00)	(0.00)	(0.00)
Exchange Indicator	-0.0005	-0.0001	-0.0015	-0.0005
	(0.00)	(0.37)	(0.00)	(0.00)
Standard Deviation	0.0591	0.0314	0.0669	0.0442
	(0.00)	(0.00)	(0.00)	(0.00)
Cumulative Return	0.0044	-0.0008	-0.0069	-0.0064
	(0.00)	(0.23)	(0.00)	(0.00)
External Crosses	-0.0030	-0.0015	-0.0031	-0.0011
	(0.00)	(0.00)	(0.00)	(0.00)
ECN	-0.0049	-0.0034	-0.0079	-0.0055
	(0.00)	(0.00)	(0.00)	(0.00)
Institution Indicators (Fixed Effects)	-	Yes	-	Yes
N	381,838	381,838	319,403	319,403
Adj-R^2	0.02	0.03	0.02	0.03

Table 6

Selected Coefficients from Quarter-by-Quarter Execution Cost Regressions

This table presents selected coefficients from cross-sectional regressions of total execution costs. The independent variables include the logarithm of market value of equity, the logarithm of relative volume (the number of shares traded divided by the geometric mean of daily trading volume over the previous five days), the inverse of the stock price on the day prior to the trading decision, an exchange indicator variable equal to one if the stock is listed on the NYSE/Amex, zero otherwise, the standard deviation of daily returns from 10 days prior to the decision date, the cumulative size-adjusted return from 10 days prior to the decision date, and indicator variables for whether the order was executed via an external cross or on an ECN. Since there is no indicator variable for broker-filled orders, it is captured by the regression intercept. The regressions are estimated for all single-mechanism orders in each quarter. Only coefficients for the intercept and indicator variables are shown.

Panel A: Coefficients from regressions without institution-indicator variables

	Buys			Sells		
	Intercept (Broker)	External Crosses	ECN	Intercept (Broker)	External Crosses	ECN
961	0.0149	-0.0038	-0.0087	0.0064	-0.0045	-0.0083
962	0.0050	-0.0028	-0.0045	0.0203	-0.0023	-0.0078
963	0.0062	-0.0063	-0.0140	0.0169	-0.0048	-0.0081
964	0.0131	-0.0025	-0.0055	0.0161	-0.0041	-0.0082
971	0.0078	-0.0041	-0.0056	0.0293	-0.0033	-0.0055
972	0.0062	-0.0045	-0.0049	0.0296	-0.0032	-0.0109
973	0.0093	-0.0029	0.0072	0.0121	-0.0053	-0.0047
974	0.0109	-0.0023	-0.0055	0.0176	-0.0018	-0.0056
981	0.0145	-0.0020	-0.0022	0.0118	-0.0008	-0.0095
Mean	0.0098	-0.0035	-0.0049	0.0178	-0.0033	-0.0076

Panel B: Coefficients from regressions with institution-indicator variables (fixed effects)

961	0.0065	-0.0027	-0.0061	0.0045	-0.0053	-0.0066
962	0.0047	-0.0016	-0.0030	0.0184	-0.0001	-0.0058
963	0.0032	-0.0005	-0.0085	0.0114	-0.0042	-0.0050
964	0.0014	-0.0008	-0.0048	0.0020	-0.0045	-0.0077
971	0.0071	-0.0013	-0.0047	0.0278	-0.0004	-0.0037
972	0.0046	-0.0043	-0.0050	0.0172	-0.0009	-0.0094
973	0.0105	0.0018	0.0066	0.0083	-0.0031	-0.0033
974	0.0086	-0.0035	-0.0039	0.0134	-0.0003	-0.0020
981	0.0108	-0.0011	0.0017	0.0165	0.0032	-0.0060
Mean	0.0064	-0.0016	-0.0031	0.0133	-0.0017	-0.0055

Table 7

Endogenous Switching Regressions

Panel A shows first stage (probit) regressions. For columns labeled "External Crossing", the dependent variable is equal to one if the order was executed via an external crossing system and zero if the order was executed via traditional brokerage. For columns labeled "ECN", the dependent variable is equal to one if the order was executed on Instinet and zero if the order was executed via traditional brokerage. The panel shows coefficient estimates, p-values in parentheses and marginal effects in square brackets. For indicator variables, the marginal effects (implied changes in probability) are computed assuming a change from zero to one. For continuous variables, the marginal effects are computed assuming a one standard deviation change from the mean of the independent variable. Panel B shows the second stage regressions, using the first stage regressions to correct for endogeneity.

	External Crosses		ECN	
	Buys	Sells	Buys	Sells
Panel A: Stage I Regressions				
Intercept	-0.3257	-0.4026	-1.0188	-1.1339
	(0.00)	(0.00)	(0.00)	(0.00)
Exchange Indicator	0.7209	0.3156	-1.2303	-0.9560
	(0.00) [0.12]	(0.00) [0.04]	(0.00) [-0.23]	(0.00) [-0.12]
Standard Deviation	-2.5588	-3.1564	1.6700	3.5173
	(0.00)[-0.55]	(0.00)[-0.50]	(0.00) [0.23]	(0.00) [0.30]
Momentum Style Indicator	-2.9171	-2.5695	0.0525	-0.01897
	(0.00) [-0.22]	(0.00) [-0.16]	(0.00) [0.02]	(0.00) [-0.02]
Value Style Indicator	-1.6138	-1.2031	0.4119	0.2488
	(0.00) [-0.19]	(0.00) [-0.11]	(0.00) [0.07]	(0.00) [0.03]
Diversified Style Indicator	-1.2548	-0.9725	0.4950	0.0204
	(0.00) [-0.29]	(0.00) [-0.17]	(0.00) [0.07]	(0.17) [0.02]
Psuedo-R^2	0.22	0.14	0.18	0.13
Panel B: Stage II Regressions				
Intercept	0.0130	0.0218	0.01393	0.0244
	(0.00)	(0.00)	(0.00)	(0.00)
Log (Market Cap)	-0.0004	-0.0011	-0.0005	-0.0012
	(0.00)	(0.00)	(0.00)	(0.00)
Log (Relative Volume)	0.0005	0.0006	0.0005	0.0007
	(0.00)	(0.00)	(0.00)	(0.00)
Inverse Price	0.0841	0.0624	0.0835	0.0512
	(0.00)	(0.00)	(0.00)	(0.00)
External Crosses	-0.0056	-0.0070	-	-
	(0.00)	(0.00)		
ECN	-	-	-0.0062	-0.0067
			(0.00)	(0.00)

Table 8

Multiple Mechanism Order Trading Intensity

This table shows the use of the three trading mechanisms to fill multiple mechanism orders. Each major row represents the number of trades required to fill an order (ranging from 2 to 10). Columns labeled 1 through 10 represent the sequence number of the trade used to fill the order. The number is each cell represents the percentage of cases in which the trading mechanism is used for a particular trade sequence. For example, the first number in the table (17.5) implies that external crosses are used as the first trade in 17.5 percent of all 2-trade orders.

		Trade Sequence									
# Trades in Order	Trading Mechanism	1	2	3	4	5	6	7	8	9	10
2	External Cross	17.5	13.2								
	ECN	12.1	11.8								
	Broker-Filled	20.4	25.0								
3	External Cross	10.5	9.9	7.3							
	ECN	7.8	8.1	7.1							
	Broker-Filled	15.0	15.3	18.8							
4	External Cross	6.7	6.9	7.1	5.2						
	ECN	5.4	5.3	5.3	5.3						
	Broker-Filled	12.7	12.7	12.6	14.4						
5	External Cross	5.4	5.4	5.2	5.3	3.6					
	ECN	4.2	4.0	3.8	4.0	4.2					
	Broker-Filled	10.4	10.6	10.8	10.7	12.1					
6	External Cross	4.0	4.3	4.2	4.1	4.0	3.0				
	ECN	3.1	3.1	3.2	3.2	3.2	3.3				
	Broker-Filled	9.5	9.2	9.2	9.3	9.3	10.4				
7	External Cross	3.6	3.7	3.7	3.6	3.4	3.2	2.3			
	ECN	2.4	2.6	2.5	2.5	2.6	2.5	2.6			
	Broker-Filled	8.2	7.9	8.0	8.1	8.1	8.5	9.3			
8	External Cross	2.8	3.2	3.1	3.0	3.0	3.1	2.8	1.8		
	ECN	2.1	2.3	2.2	2.1	2.1	2.3	2.2	2.2		
	Broker-Filled	7.5	6.8	7.1	7.3	7.2	7.2	7.4	8.5		
9	External Cross	2.3	2.4	2.6	2.6	2.5	2.7	2.4	2.2	1.6	
	ECN	2.0	1.8	1.7	1.9	1.7	1.8	2.0	1.9	1.9	
	Broker-Filled	6.7	6.8	6.8	6.5	6.8	6.6	6.6	6.9	7.6	
10	External Cross	2.4	2.4	2.3	2.3	2.3	2.3	2.3	2.3	2.0	1.6
	ECN	1.7	1.7	1.6	1.6	1.5	1.5	1.7	1.5	1.5	1.6
	Broker-Filled	5.9	5.8	6.0	6.0	6.0	6.1	6.0	6.1	6.4	6.8

Table 9

Multiple Mechanism Order Trade-Level Execution Cost Regressions

This table presents estimates of cross-sectional regressions of trade-level total execution costs on order-level and trade-level variables. Order level variables include: the logarithm of market value of equity, order size (the number of shares in the order divided by shares outstanding), the inverse of the stock price on the day prior to the trading decision, and an exchange indicator variable equal to one if the stock is listed on the NYSE/Amex, zero otherwise. Trade level variables include: relative trade size (number of shares in the trade divided by the number of shares in the order), trade sequence (the sequence number of trade in the order), the cumulative lagged implicit execution cost (defined as the price movement from the decision price (P_d) to the price of the prior trade in the order), the percentage of the order already filled and indicator variables for whether the trade was executed via an external cross or on an ECN are also included. The sample consists of all multiple mechanism orders. P-values appear in parentheses.

	Buys	Sells
Intercept	0.0294	0.0268
	(0.00)	(0.00)
Log (Market Cap)	-0.0019	-0.0014
	(0.00)	(0.00)
Log (Relative Volume)	0.0004	0.0024
	(0.00)	(0.00)
Inverse Price	0.1211	-0.0132
	(0.00)	(0.00)
Exchange Indicator	-0.0030	-0.0029
	(0.00)	(0.00)
Return Volatility	0.1268	0.2166
	(0.00)	(0.00)
Cumulative Return	0.0336	-0.0065
	(0.00)	(0.00)
Relative Trade Size	-0.0040	-0.0028
	(0.00)	(0.05)
Trade Sequence	0.0017	0.0006
	(0.00)	(0.00)
Cumulative Lagged Implicit Cost	0.0016	0.0008
	(0.00)	(0.00)
Percentage of Order Already Filled	0.0007	-0.0040
	(0.20)	(0.16)
Number of switches	-0.0009	-0.0001
	(0.00)	(0.16)
Last Trade Broker Indicator	0.0014	0.0004
	(0.00)	(0.23)
External Crosses	-0.0008	-0.0003
	(0.00)	(0.00)
ECN	-0.0021	-0.0023
	(0.00)	(0.00)
N	216,582	171,563
Adj-R^2	0.03	0.02