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Equity Trading by Institutional Investors:
Evidence on Order Submission Strategies

by

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Equity Trading by Institutional Investors: Evidence on Order Submission Strategies

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Abstract

The trading volume channeled through off-market crossing networks is growing. Passive matching of orders outside the primary market lowers several components of execution costs compared to regular trading. On the other hand, the risk of non-execution imposes opportunity costs, and the inherent "free riding" on the price discovery process raises concerns that this eventually will lead to lower liquidity in the primary market. Using a detailed data set from a large investor in the US equity markets, we find evidence that competition from crossing networks is concentrated in the most liquid stocks in a sample of the largest companies in the US. Simulations of alternative trading strategies indicate that the investor's strategy of initially trying to cross all stocks was cost effective: in spite of their high liquidity, the crossed stocks would have been unlikely to achieve at lower execution costs in the open market.

Keywords: Costs of Equity Trading, Crossing, Limit Order Trading, Institutional Equity Trading.

JEL Codes: G10, G20

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1 Introduction

There is currently a plethora of venues for trading US equities. Some fit the needs of small retail investors while others are more suited for the needs of large institutional investors and portfolio managers.[1] Using a detailed data set from a large institutional investor, we investigate the nature of competition between a principal exchange and one particular type of alternative trading system, the crossing network. A crossing network is a satellite trading place: it uses prices from the primary market and merely matches quantities. Passive matching of orders implies that several components of execution costs are low compared to regular market trading: commissions are lower and there are no spread costs or direct price impact costs. On the other hand, traders are not guaranteed execution in the network, and this may lead to significant opportunity costs. In addition, the execution probability may or may not be associated with adverse selection costs, depending on the type of traders in the crossing network.[2] Finally, because crossing networks compete for order flow, crossing participants may eventually incur implicit price impact costs as a result of reduced primary market liquidity. The largest crossing markets in the US include POSIT (ITG), NYSE crossing session I and II, and Instinet Global Crossing. In addition, there are less public internal crossing networks, many of which are the exclusive domains of institutional investors.[3]

Investigating execution costs associated with different trading methods is of obvious interest to investors seeking cost effective ways to trade. However, the functioning of alternative trading

[1]The trading venues can be broadly classified into four groups: (i) the principal exchanges, (ii) the "over the counter" (OTC) markets, (iii) other exchanges and (iv) alternative trading systems (ATS). The *principal exchanges* include the NYSE and the NASDAQ/NNM. The *OTC markets* includes the OTC bulletin board and the "pink sheet" market. The OTC bulletin board is for companies too small to list on the NNM, and the "pink sheet" market is an internet quotation service for *very* small companies operated by Pink Sheets LLC. *Other exchanges* include the AMEX, the regional exchanges in Boston, Philadelphia, Pacific, and Chicago(Midwest), and the Cincinnati Stock Exchange. Finally the *ATSs* include Electronic Communication Networks (ECNs), the Arizona Stock Exchange, and external and internal crossing networks.

[2]A stated goal of many crossing networks is to keep the identities and trades of their participants anonymous, both before and after the trades. The following example is taken from the Instinet homepage: "With Instinet Global Crossing, the process is anonymous. Pre-trade or post-trade, neither your trading partner nor other market participants will know your identity, strategy, order size, or residual size."

[3]POSIT is by far the largest crossing market and facilitated the crossing of 7.8 billion shares in 2000 and 9.3 billion shares in 2001. POSIT performs eight daily matches at the price equal to the bid-ask midpoint of the stock's primary market at fixed times which are randomized within 5 minutes to avoid manipulation. The NYSE after hours crossing session I allows participants to submit orders until 5pm when the orders are matched using the NYSE closing price for each stock. The NYSE crossing session II is designed to facilitate trading of baskets of at least 15 NYSE securities valued at USD 1 million or more. Instinet Global Crossing began in 1986 as the first electronic crossing service in the US. Currently, its operations facilitate "end-of-day crossing" and "VWAP crossing". The "end-of-day crossing" crosses orders at the closing price in the primary market, while the "VWAP crossing" is settled before the opening of the primary market and the participants are guaranteed the VWAP price during the day.

systems should also be of interest to academics, regulators and policy makers responsible for the design of securities markets. The recent success of electronic trading venues has intensified the competition for order flow faced by the traditional markets. In general, the increase in competition is positive because it lowers execution costs. Several empirical studies find that transaction costs decreased over the recent past.[4] However, increased competition for order flow has also raised some concerns related to potentially negative effects from market fragmentation. Mendelson (1987) shows that market fragmentation has both costs and benefits. The costs are related to reduced liquidity and increased volatility in each "sub-market", while the benefits are related to increased quality of the market price signals. Because crossing networks do not contribute to price discovery, the potential benefits from better price signals are lost and only the potential costs from low liquidity and high volatility are left. These costs might also eventually harm participants in crossing networks through their reliance on primary market prices. A better understanding of the nature of the competition between crossing networks and primary markets is clearly called for, including under what circumstances and for which types of assets crossing networks will coexist with other markets.

Three recent empirical papers on alternative trading systems are Fong et al. (1999), Næs and Ødegaard (2000), and Conrad et al. (2001b). Fong et al. (1999) use detailed data from the Australian stock exchange (ASX) to study the competition between exchanges and different off-market trading mechanisms, including crossing networks (POSIT Australia). Off-market trading is found to be concentrated in the most liquid stocks. The cross-sectional differences in off-market trading seem to be driven by institutional trading interest (trading volume, index inclusion), primary market liquidity (spreads, market depth, introduction of closing auction market), and the existence of a derivative market. Conrad et al. (2001b) study explicit and implicit execution costs on externally crossed orders, orders sent to ECNs, and broker-filled orders based on a large data set from the US equity market provided by the Plexus Group.[5] Conrad et al. also find that the most liquid stocks are the ones underlying the orders sent to external crossing systems. Moreover, the average total trade cost is found to be substantially lower for orders sent to external crossing systems and ECNs than for orders filled by traditional brokers.

[4]For a survey on research on transaction costs, see Keim and Madhavan (1998).

[5]The sample consist of $797,068$ orders submitted by 59 institutions between the first quarter of 1996 and the first quarter of 1998.

Both papers suggest that crossing networks provide significant competition for order flow, especially in highly liquid stocks, and considerably lower execution costs than other trading methods. On the other hand, as hypothesized in Keim and Madhavan (1998) and Hendershott and Mendelson (2000), informed traders may be present in crossing networks, offsetting their explicit cost advantage. The existence of adverse selection costs is hard to detect based on the cost measures used in the empirical literature and the data typically available to researchers, such as the data from the Plexus Group used in Conrad et al. (2001b). Using a special data set, the relation between execution probability and adverse selection is studied in Næs and Ødegaard (2000). They find that, over the month following an attempt at crossing, there is a one percent difference in risk adjusted returns between stocks that were successfully crossed and stocks that had to be purchased in the market. This finding is interpreted as evidence that the benefits of lower costs in crossing networks are mitigated by costs related to adverse selection.

In this paper, we extend the analysis of Næs and Ødegaard using the same data set. The data set includes all orders from the establishment of a US equity portfolio worth USD 1.76 billion over a 6-month period from January 1998 to June 1998. The portfolio was tracking the US part of the FTSE All World index[6], which consists of about 500 stocks, and has a very high correlation with the S&P 500 index. The data set is unique in that it contains information on the investors' complete order submission strategy, including the ex ante trading strategy, the dates on which the decision to trade was made, and the resulting fill rates of each order for different trading venues.[7] The weakness of the data set is that it is from one trader's buy orders only and covers a limited period of time. Both Fong et al. (1999) and Conrad et al. (2001b) have access to huge data sets on orders and trades and their results are therefore considerably more robust than ours. However, we show that the investor in our study is quite representative for large institutional investors in the US markets, and, because the data set is close to a "controlled experiment ", our results are exclusive.

First, we try to investigate the evidence of adverse selection more closely. On the one hand, the available empirical evidence suggest that crossing networks are competing in the most liquid

[6]The FTSE All-World index includes 49 different countries and about 2300 stocks. The aim of the index is to capture up to 90% of the investible market capitalization of each country.

[7]In many other studies, the exact investment strategy of a trader has to be estimated from the sequence of trades. This induces a selection bias in the data. It might be that the trader has decided to send the most difficult orders to brokers and the least difficult orders to crossing networks. We are not facing a selection bias problem in our data set.

stocks. If stocks that are not supplied in crossing networks are less liquid in general, then these stocks need a higher return to induce investors to hold them, and the abnormal performance of the non-crossed stocks found in Næs and Ødegaard (2000) might be explained (or partly explained) by a liquidity premium.[8] On the other hand, a liquidity and an information story need not be mutually exclusive. First, in addition to being a proxy for differences in liquidity, a wider spread may also capture a higher adverse selection component. Furthermore, other measures of liquidity, such as depth, may also capture the effect that uninformed investors withdraw from the market if they are worried about being picked off by better informed investors. Thus, a difference in liquidity between the two groups of stocks may capture the same effect as found in Næs and Ødegaard (2000), but by using different proxies for adverse selection. An interesting question in this respect, is whether the liquidity characteristics are temporary or more systematic over time. Because information asymmetries are expected to vanish relatively quickly, it would be harder to interpret a systematic liquidity difference as a sign of adverse selection, especially for the largest companies in the US market. On the other hand liquidity differences may be more permanent in nature.

We investigate these questions by calculating a whole range of liquidity and activity measures in the primary market across the groups of stocks that were supplied/not supplied in the crossing network.[9] Our results indicate that the difference in abnormal return between the two groups of stocks may be explained by both liquidity differences and private information. On the one hand, we find support for the earlier finding that crossing networks are competing in the very liquid segment of listed US equities. Stocks that are successfully crossed are significantly more liquid and more actively traded in the primary market than stocks that are not crossed. Moreover, we also show that the differences in liquidity and activity between the two groups of stocks are not date specific, but rather systematic throughout the entire period examined. On the other hand, the difference in spread between the groups of stocks is sometimes significant even though the measures of activity are equal. Following Easley et al. (1996b), this is evidence of informed trading in the stocks that could not be crossed. In addition, we show that the stocks in our sample have a very high correlation with the S&P 500 index. It is hard to believe that liquidity differences between the 500 largest and most liquid companies in the US can explain a

[8] Amihud and Mendelson (1986) show that risk-adjusted returns for stocks and bonds are increasing in their illiquidity, where liquidity is proxied by the spread.

[9] We use the crossing success of the Fund as a proxy for supply in the crossing network.

difference in abnormal performance between the two groups of stocks of 1 percent over 20 days.

Second, we want to investigate the costs of following alternative submission strategies. This is done by simulating the set of equilibrium order submission strategies for liquidity traders in the Hendershott and Mendelson (2000) model. Our simulated strategies are based on real historical price/volume paths of the stocks traded. This is possible to do because we know the dates when the decision to trade was made in addition to the desired quantities. The simulations confirm the result that crossed and non-crossed stocks have different liquidity characteristics. The stocks that are not obtained through crossing are also the most difficult and expensive stocks to acquire in the market. More interestingly, we find that the actual crossing strategy was inexpensive. Even though the crossed stocks were among the most liquid stocks on the NYSE, it would have been very hard to achieve lower execution costs by submitting limit orders for the same stocks on the same dates that they were first tried crossed.

The paper is organized as follows. In section 2, we describe our data set. We first give a short description of the investor and the crossing strategy. Then we provide some descriptive statistics establishing that the investor is indeed representative for the group of large institutional traders in the US equity market. In section 3, we discuss the relationship between execution probability and several measures of primary market liquidity. Section 4 contains a description of the methodology and results from the simulation approach. Section 5 provides our conclusions.

2 The data

Our data set contains transactions data from an actual submission strategy carried out in the US equities market by a large institutional investor, the Government Petroleum Fund in Norway (hereafter "the Fund"). To construct liquidity measures and simulate other submission strategies, we use additional transaction data from the NYSE Trades and Quotes database (TAQ), which contains all the trades and quotes for stocks listed on the NYSE, American Stock Exchange (AMEX) and NASDAQ's National Market System.

In this section, we first give a short description of the Fund and explain the opportunistic crossing strategy in some more detail. We then provide some descriptive statistics to establish that the Fund is representative for the group of large institutional traders in the US equity market.

The trading strategy

The Fund is a vehicle for investing the Norwegian Government's income from petroleum-related activities in international capital markets. Initially, the Fund was invested in foreign government securities only. However, new criteria, applying from January 1998, stated that between 30 and 50 percent of the Fund portfolio was to be invested in equities. The composition of the Fund portfolio was changed to include equities during the first half of 1998. We use transaction data for the part of the portfolio that was invested in US equities during this "buildup"/transition period.

The investment universe for the equity portfolio includes at present 28 countries in Europe, America, and Asia. US stocks represent around 29 percent of the total stock portfolio. Benchmark portfolios consist of the companies in the FTSE All-World index for these countries.[10] The US part of the index currently consists of about 480 different securities. The constituents of this index are the largest companies in the US market, and the index has a very high correlation with the S&P 500 index.

The equity portion of the total benchmark portfolio was set to 8 percent at the end of January 1998, and was then increased by another 8 percentage points at the end of each subsequent month until it reached the benchmark weight of 40 percent in June. The maximum tracking error restriction implied that the Fund was pre-committed to buy most of the stocks in the index every month.

The Fund employed four index managers to establish the portfolio. One of the index managers was chosen as "transition manager". First, the transition manager tried to find sellers among its own customers (internal crossing). If this was not possible, the manager searched for counterparties among the customers of the other three index managers or sent the order to an electronic crossing network (external crossing). Stocks that could not be crossed at all were purchased in the primary markets in addition to the residual part of the orders that were only partially crossed. According to the discussion in Ruyter (1999), this is the typical order submission strategy large index managers follow for their customers.

The total portfolio investment was USD 1751 million. The Fund went to the primary market with USD 250 million, or 14 percent, of this investment. We do not know what part of the

[10] These indices used to be called the FT/S&P's Actuaries World Index.

externally crossed orders that were sent to an electronic crossing network rather than being crossed with one of the Fund's index managers. The majority of the crossed orders, USD 1356 million of USD 1501 million, was executed internally. Market trades to complete the desired portfolio were needed on three of a total of sixteen trading dates. The highest trading volume on one date amounted to USD 300 million, or 17.1% of the total portfolio investment. Note that for the period we are considering the Fund was only buying, not selling securities. For the first two months, crossing prices were set as the primary market (NYSE/NASDAQ) closing prices that day. For the remainder of the period, prices were set as the volume weighted average price (VWAP) of trades in the primary market during the day. Figure 1 illustrates the implementation of the Fund's order submission strategy.

[Figure 1 about here.]

Robustness

Our study is based on the trades of only one institution. It is therefore of crucial importance that the investor is representative for the group of institutional investors used in other studies dealing with similar issues.

Most recent empirical studies of institutional investors' in the US equity market use data provided by the Plexus Group. These studies include Keim and Madhavan (1995, 1997), Jones and Lipson (1999a,b) and Conrad et al. (2001a,b). The Plexus Group is a consulting firm that monitors the costs of institutional trading. The data sets used in Jones and Lipson (1999a,b) are limited to trades executed in some specific firms. The most relevant samples of institutional investors with which to compare the Fund's trades are therefore the ones used in Keim and Madhavan (1995, 1997) and Conrad et al. (2001b).

Keim and Madhavan (1995, 1997) use data on all equity transactions of 21 institutional investors from January 1991 through March 1993. This data set contains a total of $62,333$ orders. The institutions vary in size. For fundamental value managers, the mean dollar value of assets under management was USD 4.8 billion, ranging from a low of USD 0.7 billion to a high of USD 12.9 billion. For index managers and technical traders, the mean dollar value of assets under management was USD 3.2 billion and USD 5.3 billion respectively.[11] In the period we are

[11] Fundamental value managers are defined as managers whose investment strategies are based on assessment

examining, the Fund was an index tracker, and, at the end of June 1998, the US equity portfolio was worth USD 1.7 billion. Conrad et al. (2001b) have a larger data set from a more recent time period. Their sample consists of $797,068$ orders submitted by 59 institutions between the first quarter of 1996 and the first quarter of 1998.

If we first look at order size, our median order is for USD 174,000. As table 1 shows, this is slightly larger than the median buy order of USD 138,000 in Keim and Madhavan (1995, 1997), and much larger than the crossed and ECN filled orders in Conrad et al. (2001b). One of the reasons for this may be that the orders routed through ECNs are generally much smaller than orders routed through crossing networks. The average dollar value of the Fund's orders of USD 386,000 is also higher than the average dollar value of the orders sent to external crossing and ECNs, but considerably lower than the average dollar value of the orders filled by brokers and multiple order mechanisms.

[Table 1 about here.]

Since the Fund was tracking the US stocks included in the FTSE All-World index, the stocks in the sample are obviously the more liquid stocks in the market. The most liquid stocks in Conrad et al.'s study are the ones underlying the orders sent to external crossing systems. These securities have an average market cap of USD 12.7 billion, while the average market cap for the stocks purchased by the Fund was USD 16.9 billion. Hence, the Fund was clearly trading in the larger companies.

One more characteristic with our data set is worth noting. Unlike most other studies, there is no selection bias in our data set. The Fund did not select what orders to send to the crossing network and what orders to send to the market based on a perception of trade difficulty.

3 Execution probability and primary market liquidity

In this section, we analyze in detail the relation between the probability of getting a stock crossed and the liquidity and trading activity in the primary market. This is possible because we know that the Fund initially tried to cross all the stocks. The data set therefore reveals the date and

of long-term fundamental values, technical managers are defined as managers whose strategies are based on capturing short-term price movements, and index managers are defined as managers who seek to mimic the returns of particular stock indexes (Keim and Madhavan (1997)).

identity of stocks that could not be crossed. Using a choice theoretic (probit) model on the probability of seeing a stock being crossed, Næs and Ødegaard (2000) find some evidence that the crossing network is removing trading volume from the primary market. However, in their model, market liquidity is only captured by company market values. This is not a particularly informative proxy for liquidity in our case, since all the stocks in the sample are relatively large.

We find that there are indeed significant differences in liquidity and activity between the two groups of stocks based on a wide range of liquidity and activity measures. Moreover, most of the liquidity and activity measures we calculate are significantly different across the groups of stocks, both on the days when they were first crossed and for the month prior to and after the actual trading dates. These results are confirmed in a probit model. After a proper orthogonalization of the independent variables, the probability of a successful cross is shown to be higher the lower the effective spread, the higher the liquidity ratio, and the higher the dollar trading volume in the primary market.

Liquidity measures

Market liquidity is a comprehensive concept that covers several transactional properties of the marketplace. Harris (1990) defines four interrelated dimensions of the concept: width, depth, immediacy and resiliency. *Width* is defined as the bid-ask spread for a given number of shares, and measures the cost per share of liquidity. *Depth* is defined as the number of shares at the bid-ask quotes, *immediacy* describes how fast a trade for a given number of shares can be executed, and *resiliency* describes how fast the price reverts to its "true" value after order flow imbalances caused by liquidity trading that has moved prices temporarily away from the "true" level. We try to capture the width, depth and resiliency dimensions by calculating several spread, volume, and volatility measures.[12]

Spread measures We consider three measures of the spread to capture the width of the market. The most commonly used spread measure is the *quoted dollar spread*. It measures the average difference between the inside quoted ask and bid for a stock over the trading day and can be thought of as the absolute "round trip" cost of trading a small amount of shares

[12]A discussion of data issues and the formulas for calculating the different liquidity and activity measures are provided in appendix A.

at the inner quotes. The *quoted percentage spread* is calculated as the quoted spread relative to the spread midpoint, or the "true" value, at each trade time. The *effective spread* takes into account the fact that trades are often executed inside (price improvement) or outside the spread ("walking the book"), and is often considered a more appropriate measure of trading costs than are quoted spreads, especially for large trades.[13] The effective spread is calculated as the average absolute dollar difference between the execution price and the bid ask midpoint multiplied by two. The spread measures the handling of a single trade, and does not capture the ability of a market structure to absorb a series of trades without perturbing prices excessively. We therefore need to supplement the spread estimates with measures of depth and volatility.

Depth and resiliency To capture market depth and resiliency, we calculate the average quoted number of shares at the inner quotes and the daily and intraday Amivest liquidity ratio.[14] The daily liquidity ratio reflects the average trading volume that would be needed to move the price by one percent during a trading day, while the average intraday liquidity ratio measures the same ability over 15 minute intervals. A high liquidity ratio indicates ability of the market to absorb large trades without affecting the price.[15] To get a broader picture of the volume and trading activity in the primary market across the groups of stocks, we also calculate total shares traded, the dollar value of shares traded, and the average trade size.

Volatility As an additional liquidity measure we calculate two measures of volatility. Volatility captures a dimension of liquidity in the sense that high depth at the inner quotes makes the trade prices less volatile since there is more depth to absorb the liquidity demand. The first volatility measure we calculate is the standard deviation of daily returns over the 10 days prior to the date when the Fund was trying to cross the stock. The other measure tries to capture the intraday volatility (15 minute return standard deviation) in each stock. When interpreting short term volatility, it is important to keep in mind that the sources of volatility may vary. From the viewpoint of a trader, high volatility can increase the probability of filling a limit order. This could attract liquidity suppliers to volatile stocks. However, high volatility may also be associated with news and informed trading so that the risk of an adverse price movement after

[13]See for example Angel (1997) and Bacidore et al. (1999).
[14]Amivest Capital Management introduced this measure of liquidity.
[15]This ratio is applied in several studies (see e.g. Khan and Baker (1993), Amihud et al. (1997)).

a fill is higher ("pick off risk"). Furthermore, informed trading would also induce the specialist to increase his spread which would make the trading costs higher. From a liquidity perspective, high volatility may also be a sign of low liquidity in the sense that the market is unable to absorb large trades without excessive price movements.

Results

In order to investigate whether stocks that are easy/hard to cross have different liquidity and activity characteristics, we split the orders into three categories on each sample date: (i) *Crossed stocks*: orders in this group were fully crossed, (ii) *Cross/Market*: orders in this group could not be fully crossed, and the residual order was purchased in the open market the next day, and (iii) *Market stocks*: orders in this group could not be crossed at all, and the whole order was therefore purchased in the open market the next day. A market trade means that the Fund was either "crowded out" by other traders who wanted to buy the stock or (the rather unlikely case) that the supply of the stock in the network was less than the size of our order.

Table 2 shows the different liquidity measures for the three order categories on two of the three dates when the Fund was not able to obtain all the required stocks in the crossing network.[16] In table 3 we have averaged the liquidity measures in table 2 according to the number of stocks traded by the Fund on each date. To examine whether our sample of stocks differs from the stocks in the S&P 500 index, we calculate the average liquidity measures for the S&P 500 index over the same dates as well as for the entire period when the Fund was trading (first half of 1998). For each liquidity measure, we perform tests for differences in means between the S&P 500 index stocks and the stocks purchased by the Fund. Except for the quoted percentage spread and the volatility measures, none of the liquidity measures are significantly different at the 1% level. Hence, the two samples have quite similar liquidity and activity characteristics. We also find that the S&P 500 stocks average for the entire half year is not significantly different from the S&P 500 stocks average on the particular dates when the Fund was trading.

[Table 2 about here.]

[Table 3 about here.]

[16] We do not report the liquidity measures separately for one of the three days because the number of orders purchased in the market on this day was too small to perform reliable statistical tests of the differences between the two groups.

The numbers in both tables strongly indicate that stocks that were easy to cross had lower spread costs than stocks that were hard to cross. The average spread difference is 22%, which is both economically and statistically significant. Interpreting spreads as a proxy for liquidity, this means that stocks that could not be crossed were less liquid than the stocks supplied in the crossing network. The group of non-crossed stocks was also less liquid measured by the intraday and daily liquidity ratios. Moreover, measured by the number of trades, the trading volume, and the number of shares traded, the trading activity was lower in the non-crossed stocks over the entire sample.[17] Measured by the standard deviation of daily returns over the 10 days prior to the crossing date, stocks that were hard to cross were more volatile than stocks that were easy to cross. However, measured by the standard deviation of the 15 minute returns on the crossing date, there was no significant difference in volatility.

Using the result in Easley et al. (1996b) that higher spread for stocks with similar trading volume is an indication of informed trading, our results give some support to the evidence of informed trading in the crossing network found in Næs and Ødegaard (2000). On the other hand, if there are systematic differences in liquidity between the two groups of stocks also on other dates, this would be less supportive to an informed trading story. To check this, we calculate the liquidity measures on each date across a window stretching from 20 business days before to 20 business days after the actual trading date. The results are shown in figure 2 with the values and tests in table 4. As can be seen from the figure and table there are systematic differences in most of the liquidity and activity measures. A notable exception is the intraday volatility measure which is quite similar between the two groups, except on the actual trade date when it is significantly higher for the crossed stocks. If a market cannot absorb trades without large price movements, the intraday volatility increases. If this is the reason for the change in intraday volatility on the trade dates, the stocks that were supplied in the crossing network did experience a decline in primary market liquidity. Note also that the quoted depth is significantly higher for the crossed stocks than for the non-crossed stocks during the days prior to the crossing date, but not significantly different on the actual crossing dates. Both these findings indicate that the crossing networks were removing a significant order flow from the primary market.

[17] This difference was insignificant for one of the trading dates, however.

[Table 4 about here.]

[Figure 2 about here.]

To investigate the relationship between primary market liquidity and the outcome of the attempt at crossing the stocks more formally, we estimate a probit model of the probability of getting a stock crossed as a function of various liquidity measures. More specifically, we assume that the probability of observing a cross is given by the model

$$y = Pr\,(\text{cross}) = F\,(\beta_0 + \beta_1 \text{eff\_spread}_i + \beta_2 \text{depth}_i + \beta_3 \text{LR}_i + \beta_4 \text{volume}_i + \beta_5 \text{vola}_i + \epsilon_i) \qquad (1)$$

where $F(\cdot)$ is the cumulative normal distribution function, and the β's are coefficients of the explanatory variables. Explanatory variables include the effective spread ("eff_spread"), the average depth at the inner quotes ("depth"), the intraday liquidity ratio ("LR"), the trading volume measured in USD ("volume"), and the standard deviation of daily returns measured over the last 10 days ("‘ vola"). The total data set contains 646 transactions, of which 214 were crosses.[18]

The model is estimated on all orders that were either fully crossed or fully filled in the primary market. The explanatory variables capture many dimensions of primary market liquidity and trading activity. The effective spread is considered the most appropriate measure of trading costs or market width. Average depth at the inner quotes is a frequently used depth measure, see for example Chordia et al. (2001). The intraday liquidity ratio captures part of the market resiliency dimension, and dollar trading volume and return volatility capture different aspects of the trading activity.[19] The estimation results are presented in table 5.

[Table 5 about here.]

When interpreting the model, we calculate slope estimates (marginal effects) at the means of the regressors ($\frac{dy}{dx}$ in table 5. These estimates predict the effects of changes in one of the

[18] We use STATA 7 to estimate the model. The intraday liquidity variable is highly correlated with the dollar volume of trading. We therefore use orthogonal versions of these two variables in the regression model.

[19] We also estimate a multinomial logistic regression model using the same set of explanatory variables, but with an additional category consisting of the partly crossed orders. Because the results from this model do not provide any additional insight, we only report the results from the probit model.

explanatory variables on the probability of belonging to a certain trade category.[20] Note also that our estimation is simplified by the fact that our data only contains buy orders; we need not adjust for the direction of trade.

The estimated probit model in table 5 confirms the result in 3 that the probability of finding a counterparty in the crossing network is positively related to the liquidity of the stock in the primary market. The probability of a cross is higher the lower the effective spread, the higher the intraday liquidity ratio, and the higher the dollar trading volume in the primary market. This implies that stocks that are easy to cross are also highly traded in the market and have low costs measured by the effective spread.[21]

To sum up, our results indicate that the most liquid and actively traded stocks in the primary market also have the highest probability of being crossed. We find some evidence that the crossing networks are removing large order flows from the primary market. Our results indicate that both liquidity differences and private information may explain the difference in ex post abnormal return between the crossed and non-crossed stocks found in Næs and Ødegaard (2000). A significant difference in liquidity between the two groups of stocks, also on other dates than the trading dates, may indicate that investors need a higher return to hold the non-crossed stocks. On the other hand, it is hard to believe that liquidity differences between the 500 largest and most liquid companies in the US can explain a difference in abnormal performance between the two group of stocks of 1 percent over 20 days as found in Næs and Ødegaard (2000). Moreover, we also find some indication that a part of the order flows removed from the primary market is from informed traders.

4 Limit order simulation

To judge whether trading in the primary market is more expensive than crossing, we need additional information on the costs of obtaining the stocks directly in the market. Since the Fund was trading in the 500 largest and most liquid companies in the US market, it could well be that a strategy of buying them directly in the market would have been less expensive than

[20] For non-linear probability models such as the probit and the logit model, we have $\frac{\partial E[y|x]}{\partial x} = f\left(\beta' x\right)\beta$ where $f(.)$ is the density function corresponding to the cumulative distribution function $F(.)$. Hence, the effects of changes in one of the explanatory variables will vary with the value of $\mathbf{x}$.

[21] Market depth and return volatility do not have significant effects on the probability of getting a stock in the crossing network.

the crossing strategy followed by the Fund.

In this section, we examine the cost of the opportunistic crossing strategy relative to alternative submission strategies. In addition to a cost comparison, the simulations allow us to obtain a measure of immediacy. This is an important dimension of liquidity which is crucial for transaction costs, and which is not directly captured by the measures used in the previous section.

Literature

Crossing networks There are two theoretical papers on crossing networks; Hendershott and Mendelson (2000) and Dönges and Heinemann (2001). There is also closely related literature on the ability of multiple competing trading venues to coexist, see for example Chowdhry and Nanda (1991), Easley et al. (1996a) and Seppi (1990).[22]

Hendershott and Mendelson (2000) develop a complex model where different types of heterogenous liquidity traders and informed traders choose between a competitive dealer market and a crossing network. There are two types of informed traders: one type with short-lived information and one type with long-lived information. Short-lived information cannot be exploited in the crossing network, but traders with long-lived information can first try trading in the crossing network and then go to the dealer market if they are not able to cross. Trader strategies are modeled as Nash strategies: each trader chooses his or her best response given her expectation of all other traders' strategies.[23] The model solution consists of multiple equilibria. All equilibria are characterized by three cutoff values that segment liquidity traders into the following four (some possible empty) sets of strategies:

- do not trade,
- trade exclusively on the crossing network,
- trade opportunistically on the crossing network, i.e. attempt to trade on the crossing network, and then go to the dealer market if you cannot get an execution in the crossing

[22] There is an extensive literature on related subjects such as (i) the costs of using electronic communication networks (ECNs) (see Barclay et al. (2001), Barclay and Hendershott (2002), Coppejeans and Domowitz (1999), Domowitz and Steil (1998)), and Hasbrouck and Saar (2001) and (ii) why some traders may want to trade outside the primary market (see Easley et al. (1996a) and Seppi (1990)).

[23] Trading decisions are based on the trader's reservation value, the spread cost, a crossing commission, the probability of getting a cross executed, and an impatience factor.

network, and

- trade only in the dealer market.

The implications on dealers' spread from the introduction of a crossing network are shown to depend on the types of traders in the market. With *no informed trading*, the negative "cream-skimming" effect dominates the positive effect of attracting new order flow. This is because the crossing network has a negative impact on the dealers' inventory and fixed costs, and because orders going first to the crossing network impose higher costs on the dealer market than those going directly to the dealer market.[24] With *short-lived* information, the low order-submission costs ensure that the introduction of a crossing network will always raise the dealers' spread. This is because the crossing network reduces the order flow from liquidity traders without affecting the order flow from informed traders. Under most circumstances, the crossing network will also increase dealer spreads when information is *long-lived*. However, this can be offset if the crossing network manages to attract sufficient new liquidity traders.

The Dönges and Heinemann (2001) model is considerably simpler than the Hendershott and Mendelson (2000) model. Competition for order flow is modeled as a coordination game. The central variable is the value of trading, or, equivalently, the disutility from non-executed orders in the crossing network. Three different settings are analyzed. In the first setting all traders face an identical and certain cost of not getting an order executed in the crossing network. In this case, there are multiple equilibria as in the Hendershott and Mendelson model. In the second setting, all traders face an identical, but unknown cost of non-execution. By introducing private signals on the value of this cost, a unique equilibrium with market consolidation is shown to exist. According to Dønges and Heinemann, assets with low price volatility and large turnovers will be traded at a crossing network, while assets with high volatility or small volumes will be traded at dealer markets. In the third setting, the cost of non-execution is no longer assumed to be common among the traders. In this case, and provided that the disutility from non-execution differs sufficiently, there exists a unique equilibrium with market fragmentation. The two models provide few unambiguous implications. Rather, they form a framework for discussing important questions.

[24]Order flow sent to the crossing network leaves the dealers with fewer orders to cover the inventory and fixed costs, leading to higher average costs per order.

Limit order simulations The probability of non-execution is a central variable for both limit orders and orders submitted to a crossing network, especially for investors who are precommited to trade. Much cited papers on the modeling of execution probability and execution time of limit orders are Angel (1994), Lo et al. (2002), and Hollifield et al. (1999).[25] Angel (1994) derives closed form solutions for the probability of limit order execution when orders arrive according to a Poisson process and prices are discrete. Lo et al. (2002) develop an econometric model of limit order execution times using survival analysis and estimate it using actual limit order data. Hollifield et al. (1999) also develop, estimate, and test an econometric model of a pure limit order market. Their model describes the tradeoff between the limit order price and the probability of execution.

There are also several interesting empirical papers on the use of limit orders. Cho and Nelling (2000) investigate the probability of limit order executions for a selection of stocks at the NYSE. They find that the probability of execution is higher for sell orders than for buy orders, lower when the limit price is farther away from the prevailing quote, lower for larger trades, higher when spreads are wide and higher in periods of higher volatility. In addition, they find that the longer a limit order is outstanding, the less likely it is to execute, and that limit orders tends to be submitted at the bid-ask midpoint. Examining order flow and limit order submission strategies in a pure limit order market (the Paris Bourse), Biais et al. (1995) find that traders' limit order strategies depend on the market conditions: traders submit more market orders when spreads are narrow and submit more limit orders when spreads are wide, as shown by Angel (1994). Harris and Hasbrouck (1996) compare the performance of limit orders relative to market orders using the TORQ database. They find that limit orders placed at the quotes or further into the market outperform market orders when the spread is larger than the tick size. They therefore argue that limit orders in some cases can reduce execution costs compared to market orders. Handa and Schwartz (1996) approach the problem from a different angle by examining the performance of limit orders versus market orders by "submitting" hypothetical limit orders on the actual price paths of the thirty Dow Jones Industrial firms traded on the NYSE. Since they are using simulations, they can also evaluate the cost of non-executed limit

[25]There is also an extensive theoretical literature on the effect of limit orders on the price discovery process as well as the relative profitability of limit orders compared to market orders. Important contributions include Foucault (1999), Glosten (1994), Easley and O'Hara (1992), Parlour (1996), Chakrevarty and Holden (1995), Seppi (1997).

orders. Their main finding is that non-execution costs are positive, but not always significant.

Simulation design

We base our simulations on the strategies followed by the liquidity traders in the Hendershott and Mendelson (2000) model, ignoring the "no trade" category. The first strategy, *opportunistic crossing*, is the actual strategy followed by the Fund. The second strategy, *pure cross*, is the case where the trader only submit orders to the crossing network. In this case, the trader has a low demand for immediacy/liquidity.

The third strategy is the case where the orders are only submitted to the market. Orders submitted to the market can be market orders or limit orders. An uninformed investor such as the Fund would generally prefer the lower costs and lower execution probability associated with limit orders to the immediacy provided by market orders. On the other hand, orders that are worked into the market may help reducing transactions costs. Domowitz (2001) shows that when the trader is "monitoring the book", and thus strategically searching for liquidity and favorable execution possibilities, a market order strategy (working the order) may reduce transaction costs considerably and reduce the price impact cost for large orders. Angel (1997) shows that about 30 percent of the market orders submitted through the SuperDot system experienced a price improvement of about USD 0.04 per share.

The best way to simulate a market order strategy would probably be to set up and estimate a dynamic model that minimizes transaction costs given the stock and market characteristics at the time of submission, such as the order flow, the depth of the limit order book, the volatility etc. The realism of such an ex post optimized strategy would be very hard to judge, however. Moreover, an "in sample" optimized strategy based on data from a limited period of time have restricted interest "out of sample". Due to the obvious difficulties in constructing a market order simulation taking into account the plethora of strategic decisions involved, we restrict our analysis to simulating different limit order strategies. In this way, we get an interesting additional liquidity statistic and a realistic "lower bound" on the implicit execution costs of alternative submission strategies in the primary market.[26]

[26]As noted by Lo et al. (2002), there will be a general bias in favor of early execution of simulated limit orders compared to actual limit orders. Moreover, the simulation does not track where in the limit order queue our order is at any point in time, only the price priority. This probably affects the fill rate and execution time of the orders in favor of the simulated orders compared to actual limit order execution.

The closest proxy to a market order strategy in our simulations is a marketable limit order strategy (MLO). A MLO strategy is a limit order strategy that is more aggressive (”in to the market”) than an ”at the quote” (ATQ) limit order strategy. The main difference between an ATQ and MLO strategy is that the limit price is set at the bid and ask prices respectively. The higher limit price of the MLO strategy increases the execution probability and speed relative to an ATQ strategy. However, this increased immediacy may come at a cost.[27]

Note that both limit orders and crossing orders have a potentially costly adverse selection component. From the buyer's perspective, a limit order is filled when there is adverse price movement and not filled when the stock value increases. Both cases may or may not be due to new information. Similarly, the probability of being a successful buyer in a crossing network increases with the number of investors on the selling side of the market. As for limit orders, if there are informed investors (with long-lived information) in the crossing network, the execution probability of a buy order decreases if the information is positive.[28]

Limit order simulations All limit order submissions are simulated using the same stocks and dates that applied when the Fund first tried to cross the orders. The first limit order simulation (LO1) is identical to the simple simulation strategy in Handa and Schwartz (1996), i.e. we do not take into account the actual order sizes traded by the Fund. In other words, we assume that only one share is traded in each stock. At the beginning of each crossing date, a limit order is submitted with a limit price equal to the opening bid-quote (”at the quote” limit order strategy) for each stock that the Fund tried to cross. If a trade with a price lower than the limit order price is observed during the day, the order is assumed to be filled. If an order is not filled, we assume that it is executed at the opening price the next day. Thus, we implicitly assume an investor who is pre-committed to trade the stocks. During the transition period, the Fund was tracking an index with a limit on the relative volatility between the transition portfolio and the benchmark. Thus, even though the trades probably could have been worked more carefully into the market the next day, the penalty for unexecuted orders which follow from our assumptions is not completely unrealistic. Because we are ignoring order size, the first

[27] The cost differential between the two types of strategies may vary over time depending on market conditions. Obviously, the execution probability of a marketable limit order is lower in a bear market relative to a bull market.

[28] Næs and Ødegaard (2000) find evidence that the Fund was “crowded out” by informed investors on the same side of the market.

limit order simulation constitutes a lower bound on transaction costs.

In the second simulation (LO2), we split the actual order size into suborders. The number and size of the suborders are determined by the average order size traded in the stock at $t-1$. In addition, we have one residual suborder of a smaller size (if necessary). All the suborders are assumed to be submitted sequentially. Thus, at the beginning of the trading day, the first suborder is submitted as an "at the quote" limit order. A suborder is assumed filled if the observed execution price is less than the limit-price without taking into account the size of the suborder. When a suborder is filled, the next suborder is submitted at the bid quote following the fill ("chasing the market"). Unfilled orders are assumed to be executed at the opening price the next day.[29]

The third limit order simulation (LO3) is the most realistic because here we also take into account the size of the suborders. The strategy is similar to LO2 except that we also examine whether the size of the suborder is less than or equal to the size of the actual order executed in the market. A suborder is only assumed filled if the observed execution price is less than the limit price *and* the size is equal to or larger than the size of our order. Due to price priority, our hypothetical order would under most circumstances execute before the observed trade since our order would be the last in the queue at our limit price.

A problem with this type of simulation is that the hypothetical orders most likely would have changed the structure of the market in the stocks if they had actually been submitted. Furthermore, Lo et al. (2002) note than the results from simulations with actual limit-order data underestimate the execution times in a real world trading situation. The execution time for a real limit order is a function of the order size, the limit price and the current market conditions, and a trader would generally vary the order submission strategy based on current and expected market conditions. Such factors are obviously very hard to capture in a simulation approach like ours. On the other hand, we do know the order sizes of the actual strategy and we do take these into account in the LO2 and LO3 simulations, which probably reduces the bias.

Pure crossing simulation A pure crossing strategy is defined as a strategy where the trader only trades in the crossing network. According to Hendershott and Mendelson (2000), the low liquidity preference traders who would follow this type of strategy are most likely to benefit

[29]The unexecuted orders are assumed submitted to the pretrade auction without affecting the opening price.

from the existence of a crossing network. To simulate this strategy we use the actual price data for the stocks that the Fund was able to cross. For the stocks that the Fund was not able to cross, we assume crossing over the next 10 days. Hence, the opportunity costs are simulated, but the identity of stocks that could not be crossed are not. The choice of a 10-day trading window for calculating the opportunity costs is based on the statistics on order fills in Conrad et al. (2001b): the 95th percent confidence interval for getting an order filled in an external crossing system is reported to be 10 days. Thus, on each crossing date we take the stocks that did not cross and assume that they were crossed over the next 10-day period to the equally weighted close price over the 10-day period.

Measuring trading costs

In order to compare the performance of different submission strategies we must apply a measure of transaction costs. Current empirical academic literature on transaction costs are to a large degree based on versions of a theoretical measure which was first proposed by Treynor (1981) and which Perold (1988) later called the implementation shortfall. The implementation shortfall is defined as the difference in performance between the portfolio of actual trades and a matching paper portfolio in which the stock returns are computed assuming that the trades were executed at the prices prevailing on the date of the decision to trade. In this way, both explicit cost components such as brokers fees, and implicit components such as spread costs, price impact costs, and costs related to delayed or uncompleted trading (opportunity costs) are captured. The approach also overcomes the problem of measuring costs on an individual trade basis when the order consists of a package of sub-trades [30]. Keim and Madhavan (1998) and Conrad et al. (2001b) suggest an empirical version of the implementation shortfall approach:

$$\begin{aligned} \text{total cost} &= \text{explicit cost} + \text{implicit cost} \\ &= \left\{\frac{\text{commission per share}}{P_d}\right\} + \left\{[\alpha \frac{P_a}{P_d} + (1-\alpha)\frac{P_{d+x}}{P_d}] - 1\right\} \end{aligned} \tag{2}$$

where P_d is the closing price for the stock on the day before the decision to trade, P_a is the average price for all the executed trades in the order, α is the fill rate, and P_{d+x} is the closing

[30] Much of the relevant research on the measurement of transaction costs is summarized in Keim and Madhavan (1998)

price x number of days after the decision date, i.e. the unfilled portion of an order is assumed settled x days after the decision date.

We use the same measure as in Conrad et al. (2001b), except that we assume that the non-crossed orders in the pure crossing strategy are settled at the average of the closing prices over the x days after the decision date. In addition, since we cannot easily get good estimates for the explicit costs related to the trades that we simulate, the cost comparison is made on the basis of implicit costs only. Thus, our cost comparison is *not* based on total execution costs. A more serious problem is related to the limited number of trading days in our data set. The implicit cost estimate is intended to account for the price impact of orders. However, the price difference between P_a and P_d will also be affected by general market movements between the two observation times. Essentially, the measure assumes that the main source of price impact is our order. When we look at averages for trades on many different dates, this is not a big problem, because the market movement will tend to wash out in the average[31]. However, if we look at trades concentrated on a few dates, the general market movements at these dates will affect the measured costs. As we shall see, this is a particular problem for the market orders in our data set because they are concentrated on only three days.

Empirical studies document that the magnitude of different cost components vary with factors such as order size, intraday timing of the trade, stock liquidity, market design and investment style. Hence, to measure costs properly, detailed data on the entire order submission process is required. For the actual submission strategy followed by the Fund, we have access to such data. For the simulated strategies, however, the results will necessarily be driven to some extent by our own assumptions.

Results

For the orders that were executed on the day following the initial attempt at internal crossing, the total cost should be decomposed into one component associated with the delay of the order in the internal crossing network, and one component associated with the final execution in an external crossing network or in the primary market. Table 6 decompose the implicit costs for the Fund's order submission strategy into these two components.

[31]Keim and Madhavan (1997) show that the average daily return on stocks is small compared to the price impact from a trade.

[Table 6 about here.]

Including the delay costs, the average implicit cost for all crossed orders was 0.11 percent, and the average implicit cost for all market orders was -0.74 percent. This implies an average implicit cost for all orders of -0.03. Some care should be taken when interpreting the negative implicit costs for the market orders. Because the orders purchased in the primary market are concentrated on three trading days only, the cost estimates are quite sensitive to the market movements on these days. Ignoring the delay component, the average implicit cost for all market orders was about 0.25 percent. The Fund incurred delay costs for market orders on one occasion. The market went markedly down on this day, leaving the Fund with an implicit delay cost for the non-crossed orders of -1.79 percent. Because the non-crossed orders had to be bought in the market on the following day, an average additional cost of 0.48 percent was incurred, giving a total implementation shortfall cost of -1.31 percent.

Measured over some time, the daily market movements are small compared to the price impact costs, as shown in Keim and Madhavan (1997). Hence, for large samples, adjusting for daily market returns does not make much difference. However, in our case, the cost measure is likely to be largely driven by the market movement. Keim and Madhavan (1997) argue that one should *not* try to adjust for market movements because they are a part of the timing cost for the order submission strategy. If so, the average implicit cost associated with the delay of orders in the private internal crossing network of -0.121 percent should be interpreted as a negative timing cost. On the other hand, the fact that the drop in market values on one of the trading days was large enough to have a significant effect on the total implementation shortfall cost of the actual strategy, suggests that the true costs of opportunistic crossing may be underestimated.

What the discussion above highlights most of all is that cost measures based on the implementation shortfall over a few days should be interpreted with great caution. Due to the non-synchronous nature of the Fund's market trades relative to the close-to-close returns on the SP 500 index, a correct adjustment for the market movement would involve the actual timing of the trades during the day as well as the intraday SP 500 returns. None of which are easily obtainable. What we want is to set up a horse race between the opportunistic crossing strategy and certain alternative order submission strategies. If the alternative strategies cannot beat the strategy when the negative delay costs are excluded, they surely cannot beat the strategy when these costs are included. In Table 7, we have therefore compared the estimated execution costs for the simulated strategies with the actual average execution costs *excluding* the delay costs.[32] That is, all cost estimates in the table are in percent of the closing price on the day before the trade.[33]

[Table 7 about here.]

Examining the execution costs for the simulated strategies in table 7, we find that neither the pure crossing strategy nor the two first limit order strategies (LO1 and LO2) have significantly different execution costs from the opportunistic crossing strategy. Thus, not even the most simplistic and unrealistic limit order simulation (LO1), which constitute our "lower bound" on primary market execution costs, is able to significantly beat the opportunistic crossing strategy. The most realistic limit order strategy (LO3) is significantly more expensive than the opportunistic crossing strategy, with costs of about 0.24 percent. In addition, we have not taken into account that the explicit costs in crossing networks are lower than in the primary market. Hence, the total execution costs would overwhelmingly favor the opportunistic crossing strategy, or potentially the pure crossing strategy.

An additional choice variable for an investor is the aggressiveness of the limit order. In figure 3, we have plotted the implicit costs for the three limit order strategies LO1, LO2 and LO3 assuming more or less aggressive limit prices. In addition, the figure includes the implicit cost (ex delay costs) of the opportunistic crossing strategy (straight line across all aggressiveness levels). The ATQ limit order strategy is at 0 on the x-axis (indicating that the limit price is 0 ticks away from the opening bid). The MLO strategy is located between 1 to 3 ticks away from the bid, depending on the spread and tick sizes of the different stocks at the time of submission. An interesting observation in figure 3 is that the LO1 line forms a lower bound on execution costs. In addition, we see that the implicit costs across all strategies and aggressiveness levels reaches a minimum around 0 and 1 ticks away from the opening bid. This is in line with the results in

[32] What we ignore, however, is that the high volatility in the market at this particular day may have affected the outcome with respect to what stocks we were able to achieve in the crossing networks, as suggested in Domowitz (2001).

[33] Næs and Ødegaard (2000) also estimate the explicit costs for the Fund's strategy. The equally weighted average explicit costs for all orders were 3 percent. For the crossed orders and the non-crossed orders, the explicit costs were 3 percent and 5 percent respectively.

Harris and Hasbrouck (1996), that limit orders generally are cheaper than market orders. More specifically, they find that when the spread is larger than one tick, limit orders placed in the market (improving the best bid or ask) perform better with respect to costs. Furthermore, Cho and Nelling (2000) show that the majority of limit orders are in fact submitted at the bid-ask midpoint.

[Figure 3 about here.]

By looking more carefully at the crossed/non-crossed groups, we find that the non-crossed stocks have the highest execution costs regardless of submission strategy. In the previous section, we found that stocks that are not supplied in the crossing network are less liquid than stocks that are easily crossed. The higher execution costs for these stocks support this finding: these stocks are also the most difficult to fill in the primary market. Note also that the opportunity costs constitute a large part of the execution costs for orders in these less liquid stocks. Since unfilled limit orders generally are for stocks that rise in value, these orders are penalized by the execution at the opening price the next day. This result, together with the high costs found for the pure crossing strategy, supports the finding in Næs and Ødegaard (2000) that the stocks bought in the market had a high ex post return.

Overall, our results strongly favor the opportunistic crossing strategy as a cost-effective submission strategy, especially when the difference in explicit costs between the crossing network and primary market is taken into account. Furthermore, it is important to recognize that the orders examined here are for the most liquid and largest companies in the US. Thus, even the stocks with the potentially lowest execution costs in the primary market would have been cheaper to obtain in the crossing network.

In table 8, we have calculated the fill rates for all orders in panel (a), and the fill rates across groups of orders in panel (b). The execution times (in minutes since open) for the simulated strategies are shown in panel (c). As expected, the fill rate decreases and the execution time increases as we impose more restrictions on the limit order strategy. It is interesting to note that the fill rates across groups of stocks in panel (b) are higher for the non-crossed orders than for the crossed orders. Thus, even though the fill rate is higher for the non-crossed stocks, the execution costs are higher. This indicates that the stocks in the non-crossed group that were not filled in the limit order simulation had a very high opportunity cost. This result provides further support to the information hypothesis in Næs and Ødegaard (2000).

[Table 8 about here.]

5 Conclusion

In this paper, we use data from an actual order submission strategy using crossing networks to investigate execution costs and primary market liquidity. The data includes all orders from the establishment of a US equity portfolio worth USD 1.76 billion in the period from January 1998 to June 1998. The investor in our study was following an "opportunistic" crossing strategy, meaning that an attempt was made to cross all stock orders initially, and residual orders were purchased in the open market. Because we know the identity of stocks and timing of stock orders that failed to be executed in the crossed network, we can investigate whether stocks that are supplied in crossing networks and stocks that can only be traded in the market have systematically different characteristics. In addition, the costs of alternative, more traditional, submission strategies can be estimated and compared.

By calculating several measures of liquidity for the different groups of stocks in the data set, we show that there are significant differences in liquidity between stocks that are crossed and stocks that have to be bought in the market. For some stocks, spreads are significantly different even though the trading volume in the two groups of stocks was similar. According to the market microstructure literature, this might be an indication of informed trading in the stocks that could not be executed in the crossing network, a result which is also suggested in Næs and Ødegaard (2000). We also find, however, that there are systematic differences in liquidity between the two groups of stocks on other dates than the trading dates of the actual crossing strategy. This result suggests that there are systematic differences in the characteristics of the two groups of stocks that are not related to private information.

To evaluate the performance of the actual crossing strategy against other submission strategies, we perform limit order simulations on transactions data from the NYSE. The simulations can also be viewed as an additional measure of trading difficulty. The non-crossed orders turn out to be significantly more expensive than the crossed orders across all simulations. Hence, the stocks that the Fund could not get in the crossing network would also have been the most difficult to buy in the market. We also show that it would have been very hard to beat the actual opportunistic crossing strategy. The only simulation which gives us a lower implicit cost estimate is when we completely ignore the size of our orders. However, the explicit cost differential between the crossing network and regular market would probably even this difference out. Finally, it should be stressed that the significant differences found in crossing probability, liquidity and primary market execution costs are for the 500 largest and most liquid stocks in the US market.

A Calculation of liquidity and activity measures

To calculate the liquidity statistics in the primary market for all securities traded by the fund we use the TAQ database (NYSE Trades and Quotes database). However, before we perform the calculations, the data has to be filtered to remove erroneous records both in the quotes file and the trades file.

Data issues and filtering

Quotes data

All the spread measures are calculated with respect to the inside quotes (best bid and ask) reported in the TAQ database between 9:30 and 16:00. There are several filters applied to "clean" the data. We mainly use the quote conditions (MODES) in the TAQ data[34] to do this. An observation is removed if one of the following conditions applies;

- **Closing quote** The last quote from a participant during the trading day (Mode=3)
- **News dissemination** A regulatory halt when price sensitive news arrives (Mode=4)
- **Fast trading** Indicating that there is extreme activity (quotes are entered on a "best efforts" basis) making the time stamps unreliable (Mode=5)
- **Order imbalance** A non-regulatory trading halt due to large order imbalances (Mode=7)
- **Non-firm quote** A regulatory halt when the Exchange is unable to collect, process and disseminate quotes that accurately reflect market conditions (Mode=9)
- **News pending** A regulatory trading halt or delayed opening due to an expected news announcement (Mode=11)
- **Trading halt due to related security** A non-regulatory halt used when there is news related to one security which will affect the trading and price in another security (Mode=13)

In addition we remove quotes where the bid price is larger than the ask price, quotes are negative, or the average quoted spread is zero over the trading day. Also quotes with a price higher than USD 10,000 are removed both due to possible errors as well as to remove securities

[34] A more detailed description can be found in the TAQ User Guide which can be downloaded from the NYSE homepage at http://www.nyse.com/marketinfo/marketinfo.html

with extreme prices which could affect our statistics. Lastly, when quotes from several different exchanges are reported at the same time (down to the second), we use the lowest ask or highest bid among these as a proxy for the NBBO (National Best Bid and Offer).

Trades data

The trades reported in TAQ may contain corrections and errors. If so, the record has a *Correction Indicator* (Corr) attached to it. The requirement is that a trade must have a correction value less than 2 (Corr < 2). If Corr=0, then the trade record is a regular trade that was not corrected, changed, cancelled or was erroneous. If Corr=1, then the observation was later corrected, but the record contains the original time and the corrected data for the trade. If Corr > 2, then the record is either out of time sequence, cancelled due to error or cancelled due to wrong timestamp. Thus, we remove all records with Corr ≥ 2.

There are also *Sale Conditions* (Corr) connected to each trade. We apply a filter removing records with conditions that make the timing and reliability of the records questionable. A record is removed if one of the following conditions applies;

- **Bunched sold** A bunched trade not reported within 90 seconds of execution (Cond=G)
- **Sold last** A trade reported later than the actual transaction time (Cond=L)
- **Opened last** An opening trade with delayed reporting (Cond=O)
- **Sellers option** Delivery date is between 2 and 60 days after the trade (Cond=R)
- **Pre- and Post-Market Close Trades** A trade that occurred within the current trading day, but is executed outside of the current market hours (Cond=T)
- **Sold sale** A transaction that is reported to the tape at a time later than it occurred and when other trades occurred between the time of the transaction and its report time (Cond=Z)
- **Crossing session** NYSE Crossing Session matches (Cond=8 and 9)

After the filtering is performed, we use the remaining quotes and trades to calculate the following liquidity and activity measures.

Spread measures

Effective spread

The effective spread takes into account the transaction prices (and accounts for the fact that many trades are executed within the quoted spread due to price improvement). The number of trades in the security, i, on date, t, is denoted by $N_{i,t}$. The index τ defines the time of the day when a trade is observed, $P_{i,\tau}$ is the trade price, and $bid_{i,\tau}$ and $ask_{i,\tau}$ is the bid and ask, respectively, at the time of the trade. The first valid trade is normalized to $\tau = 1$. Then, for security i on date t, the average effective spread is calculated as,

$$ES_{i,t} = \frac{1}{N_{i,t}} \sum_{\tau=1}^{N_{i,t}} \left\{ 2 \mid P_{i,\tau} - \frac{ask_{i,\tau} + bid_{i,\tau}}{2} \mid \right\}$$

The effective spread takes into account the relationship between execution price and quoted spread, and is often considered a more appropriate measure of trading costs than quoted spreads, especially for large trades.

Quoted dollar spread

The average quoted dollar spread is defined as the average difference between the inside quoted ask and bid for a firm over the trading day. The quoted dollar spread is calculated with respect to each trade observed at time τ. The inner ask and bid is defined as $ask_{i,\tau}$ and $bid_{i,\tau}$ respectively, and $N_{i,t}$ is the total number of trades in security i during the trading day t. Thus, the quoted dollar spread is calculated as,

$$QS_{i,t} = \frac{1}{N_{i,t}} \sum_{\tau=1}^{N_{i,t}} (ask_{i,\tau} - bid_{i,\tau})$$

Quoted percentage spread

The quoted percentage spread calculates the absolute spread relative to the spread midpoint at each valid trade record τ. Thus,

$$RS_{i,t} = \frac{1}{N_{i,t}} \sum_{\tau}^{N_{i,t}} \left\{ \frac{ask_{i,\tau} - bid_{i,\tau}}{(ask_{i,\tau} + bid_{i,\tau})/2} \right\}$$

Volume and depth measures

It is widely argued that spreads should not be examined in isolation when using it as a liquidity measure. This is because liquidity shocks both widen spreads as well as reduce depths. Furthermore, spreads may also widen as a response to adverse selection without liquidity necessarily decreasing. Therefore, we also look at volume and depth measures.

Trading Volume (Shares)

The total number of shares traded in security i during day t.

$$VOL\_shares_{i,t} = \sum_{\tau=1}^{N_{i,t}} Q_{i,\tau}$$

Trading volume (USD)

The total dollar value of trades during day t in security i.

$$VOL\_USD_{i,t} = \sum_{\tau=1}^{N_{i,t}} Q_{i,\tau} \cdot P_{i,\tau}$$

Trades

The total number of trades during day t in security i.

$$Trades_{i,t} = \sum_{\tau=1}^{N_{i,t}} \tau_i$$

Trade size

The average trade size in USD 1000 on day t in security i.

$$Trade\_size_{i,t} = \frac{VOL\_USD_{i,t}}{Trades_{i,t} \cdot 1000}$$

Quoted depth

The quoted depth is calculated as average of the quoted bid and ask depths during the day t in security i,

$$QD_{i,t} = (\bar{q}^{bid}_{i,t} + \bar{q}^{ask}_{i,t})/2$$

where $\bar{q}^{bid}_{i,t}$ and $\bar{q}^{ask}_{i,t}$ is the average depth on the bid- and the ask-side respectively in security i on day t.

Liquidity ratios and volatility measures

Daily Liquidity Ratio

The Amivest Liquidity Ratio is one type of liquidity measurement which represents the dollar value of trading associated with a one percent change in the share price. Amivest is the "creator" of this liquidity measurement. The liquidity ratio measures the average trading volume necessary to move the price by one percent during a trading day. We calculate the average daily liquidity ratio over the 10-day period prior to the Fund's trading date, t_0. The daily liquidity ratio for security i on date t is thus calculated as,

$$LR(D)_{i,t} = \frac{1}{10} \sum_{t=t_0-11}^{t_0-1} \frac{VOL\_USD_{i,t}}{|\%r_{i,t}|} /1000$$

where $|\%r_{i,t}|$ is the absolute "midpoint return" over day t calculated using the bid-ask midpoints at opening and closing to avoid biases with respect to the bid-ask bounce. $VOL\_USD_{i,t}$ is the total USD trading volume in security i on date t.

Intraday Liquidity Ratio

To measure liquidity on one date, we also calculate the liquidity ratio using intraday data. To do this, we first discretisize the data to get a common time frame. Consistent with several other studies we use 15-minute windows, starting from 9:30am until 16:00pm. Thus, we have 26 15-minute intervals during each trading day. During each interval, denoted by ω, we calculate the midpoint returns using the bid-ask midpoint price at the beginning (or closest to the beginning) of each window. Thus, $\omega \in [1, 26]$, and the average ratio for security i on date t is calculated as,

$$LR(I)_{i,t} = \frac{1}{26} \sum_{\omega=1}^{26} \frac{VOL\_USD_{i,\omega}}{|\%r_{i,\omega}|} / 1000$$

where $VOL\_USD_{i,\omega}$ is the total USD volume traded in security i in window ω, and $|\%r_{i,\omega}|$ is the 15-minute absolute midpoint return over window ω. Generally, the liquidity ratio measure assumes that there is a linear relationship between the trade size and price change which is not necessarily the case. In addition, the ratio is positively correlated with the general price trend in the market and negatively correlated with volatility.

Average 10-day volatility

Calculates the 10-day average volatility prior to the actual trading date (t_0) as,

$$V(D)_{i,t} = \sqrt{\frac{1}{10} \sum_{t=t_0-11}^{t_0-1} (r_{i,t} - \bar{r}_i)^2}$$

where $r_{i,t}$ is the return on day t and $\bar{r}_i$ is the average return over the 10-day period prior to the actual crossing date.

Intraday volatility

When calculating intraday volatility, we use the same discretization as for the intraday liquidity ratio calculations described above. Thus, we calculate the volatility of 15-minute returns over the trading day, using the bid-ask midpoint price at the beginning of each window, such that,

$$V(ID)_{i,t} = \sqrt{\frac{1}{26} \sum_{\omega=1}^{26} (r_{i,\omega} - \bar{r}_{i,t})^2}$$

where $r_{i,\omega}$ is the midpoint return over 15-minute window ω, and $\bar{r}_{i,t}$ is the average return over all windows during trading day t in security i.

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Figure 1: **Implementation of the Fund's Order Submission Strategy**
The figure illustrates the implementation of the order submission strategy followed by the Fund. First, the transition manager tried to find sellers among its own customers (internal crossing). If this was not possible, the manager searched for counterparties among the customers of the other three index managers hired by the Fund or sent the order to an electronic crossing network (external crossing). Stocks that could not be crossed at all were purchased in the primary markets in addition to the residual part of the orders that were only partially crossed. The overall part of the orders were crossed internally. All orders were executed within two days after the decision to trade. The numbers in parentheses are percent of total portfolio investment (USD 1 751 billion).

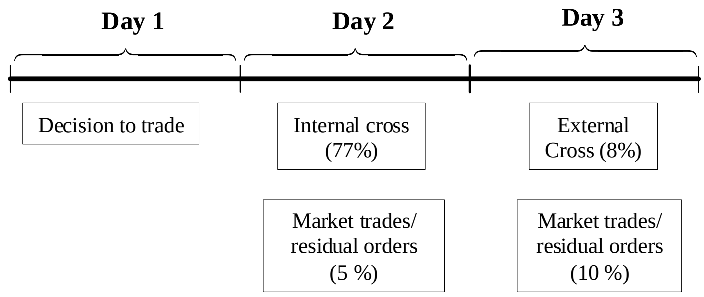

Figure 2: **Time series average of liquidity and activity measures**

The figures show average time series plots of the different liquidity and activity measures. The actual trading days are aligned at t=0. From the figures there seem to be a systematic difference in both liquidity and activity over time between the group of stocks that were fully crossed and those that were not crossed at all. Similar plots of the measures around the separate dates show the same systematic patterns.

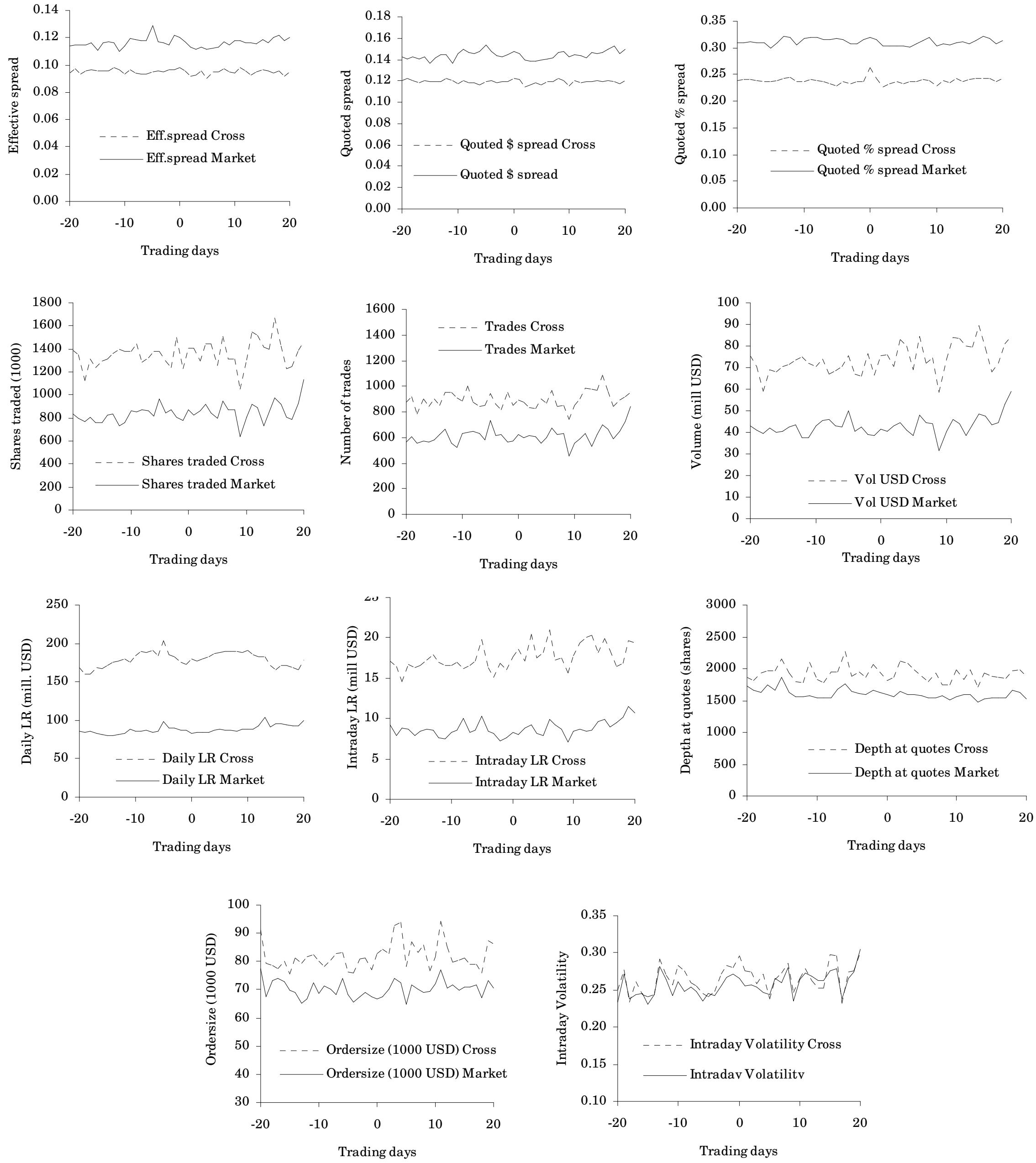

Figure 3: **Limit order simulation for varying aggressiveness levels.**
The figure shows the implicit costs of the three types of limit order simulations we perform (LO1, LO2 and LO3) for varying aggressiveness levels, where aggressiveness is measured in ticks relative to the "at the quote" limit order strategy. A limit order aggressiveness of 0 indicates that the limit order price is set at the opening bid price. An aggressiveness larger (lower) than 0 means that the limit order price is set x number of ticks higher (lower) than the opening bid price. The horizontal line shows the implicit cost of the opportunistic crossing strategy excluding delay costs.

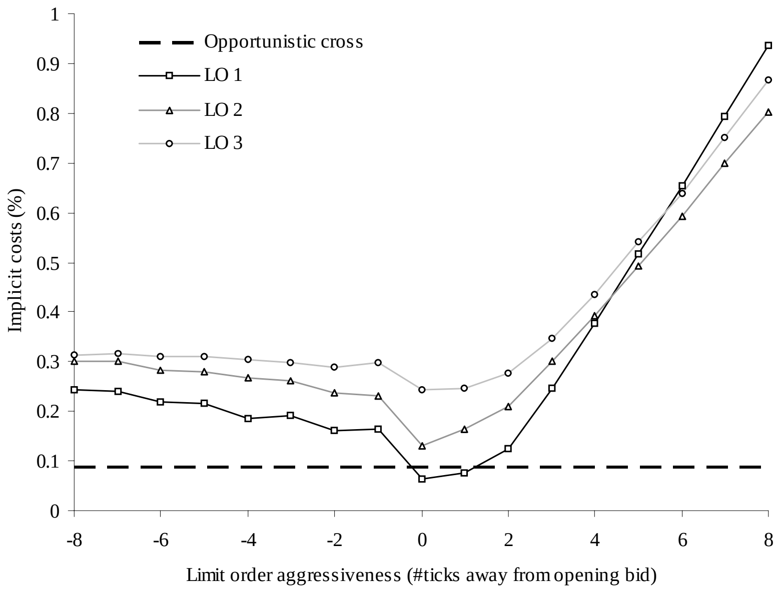

Table 1: **Descriptive statistics for traded securities**

In this table, we make a comparison of the data used in this study and in Keim and Madhavan (1995, 1997) and **?**. In our study and in Keim and Madhavan (1995,1997), the numbers are for buyer-initiated trades only. "Multiple mechanism orders" in the Conrad et al. paper are orders in which more than one of the three trading mechanisms (brokers, ECNs or external crossing systems) are used to fill the order. Market cap values are in USD billion. "Listed %" is the percentage of total orders that is in listed stocks. "n" is the total number of orders.

	Order size				Liquidity			
	Dollar value		No. of shares		Market cap		Listed	n
	mean	median	mean	median	mean	median	%	
Our study								
All orders	386	174	6 898	3 800	16.9	7.5	100	4 200
- Cross	396	177	7 013	3 800	17.6	7.8	100	3 494
- Market order	339	157	6 329	3 550	13.6	6.1	100	706
KM [1995,1997]								
All orders		138		4 800		1.1	82.6	36 590
Conrad et al. (2001b)								
All orders								723 998
- External cross	187	45			12.8		> 90.0	112 159
- ECN's	194	53			3.0			51 127
- Broker filled	1474	137			11.1			560 712

Table 2: **Liquidity in the primary market on the trading dates**

The table shows different measures of liquidity and activity in the primary market on the dates when the Fund did not fill all orders in the crossing network. "Crossed stocks" means that the whole order of a stock was crossed. "Crossed/Market" means that part of the order was crossed and part of the order had to be purchased in the open market. "Market stocks" means that the stock could not be crossed at all. The calculation and explanation of the different measures are found in Appendix A. The t-stat and p-value are the test statistics of a two-sided t-test, where the null is that the mean for the "Crossed stocks" and "Market stocks" stocks are equal. The test depends on whether the population variances of the two groups are equal or not. If the variances are equal, then the t-stat is calculated as $t = (\bar{x}_c - \bar{x}_m)/\sqrt{s^2(1/n_c + 1/n_m)}$ where $\bar{x}_c$ and $\bar{x}_m$ are the means for the two groups respectively, n_c and n_m are the number of stocks in each group while s^2 is the pooled standard deviation calculated as $s^2 = [(n_c-1)s_c^2 + (n_m-1)s_m^2]/[n_c+n_m-2]$, where s_c^2 and s_m^2 are the standard deviation of measure for the cross and market stocks respectively. We use the SAS package to perform all tests. If the variances are significantly different, the standard approximation supplied in SAS is used. For the *Daily volatility* measure, we use an F-test to test for differences in variance between the two groups, where the null is that the ratio of the two sample variances is equal to 1.

DATE 1	S&P 500 stocks	Fund stocks	Crossed stocks	Market stocks	Diff. test p-value	Crossed/ Market	Diff. test p-value
Spread measures							
Effective spread	0.1112	0.1063	0.0931	0.1118**	0.0103	0.0893	0.6514
Quoted USD spread	0.1322	0.1315	0.1135	0.1395**	0.0069	0.0910	0.0969
Quoted % spread (midp.)	0.3270	0.2566[a]	0.1916	0.2852**	<.0001	0.1200*	0.0111
Volume measures							
Trades	807	861	1317	575**	0.0002	4985**	<.0001
Shares traded (1000)	1180	1274	2039	868**	0.0001	5487**	0.0007
Volume (USD mill.)	61	67	116	39**	<.0001	434**	<.0001
Trade size (USD 1000)	79	85	88	67**	0.0011	103	0.6159
Liquidity ratios and depth							
Daily LR (USD mill.)	117	148	293	76**	<.0001	785	0.1221
Intraday LR (USD mill.)	13	16	28	8**	<.0001	103	0.0576
Depth at quotes (shares)	1198	1841	2126	1692	0.0965	3351	0.1942
Volatility and return							
Daily volatility (10-day average std.dev)	0.0275	0.0256[a]	0.0225	0.0265**	<.0001	0.0342**	<.0001
Intraday volatility (15 min. % std.dev)	0.2601	0.2367[a]	0.2573	0.2296*	0.0307	0.2044*	0.0361
N stocks	454	368	100	261		7	

DATE 2	S&P 500 stocks	Fund stocks	Crossed stocks	Market stocks	Diff. test p-value	Crossed/ Market	Diff. test p-value
Spread measures							
Effective spread	0.1174	0.1139	0.1027	0.1327**	0.0082	0.1039	0.7636
Quoted USD spread	0.1396	0.1420	0.1299	0.1605*	0.0445	0.1326	0.5257
Quoted % spread (midp.)	0.3903	0.3375[a]	0.3255	0.3724*	0.0380	0.3136	0.5391
Volume measures							
Trades	737	678	515	692	0.1830	763*	0.0447
Shares traded (1000)	1015	929	847	875	0.8390	1025	0.2390
Volume (USD mill.)	53	48	40	46	0.5469	54	0.1914
Trade size (USD 1000)	68	67	78	66**	0.0065	67	0.0917
Liquidity ratios and depth							
Daily LR (USD mill.)	100	101	81	92	0.5182	120	0.0598
Intraday LR (USD mill.)	10	9	8	8	0.9397	11	0.2481
Depth at quotes (shares)	1572	1506	1524	1464	0.7546	1532	0.9676
Volatility and return							
Daily volatility (10-day average std.dev)	0.0220	0.0263[a]	0.0250	0.0271**	0.0025	0.0263*	0.0449
Intraday volatility (15 min. % std.dev)	0.3494	0.3217[a]	0.3298	0.3220	0.6551	0.3167	0.4233
N stocks	454	478	114	171		193	

[a] Equality of the measure between the S&P 500 and Fund stocks is rejected at the 5% level.
* Equality of the measure between the Crossed and Non-crossed stocks (Market stocks) is rejected at the 5% level.
** Equality of the measure between the Crossed and Non-crossed stocks (Market stocks) is rejected at the 1% level.

Table 3: **Average liquidity over all stocks**

The first and second columns in the table show the cross-sectional average measures for the S&P 500 constituent stocks during the first half of 1998 (S&P 500 June-July) and on the same dates as for the Fund trades (S&P 500). The third column (Fund) is the cross-sectional average for all the stocks that the Fund traded on the two dates. The t-stat and p-value are the test statistics of a two-sided t-test, where the null is that the mean for the "Crossed stocks" and "Market stocks" stocks are equal. The test depends on whether the population variances of the two groups are equal or not. If the variances are equal, then the t-stat is calculated as, $t = (\bar{x}_c - \bar{x}_m)/\sqrt{s^2(1/n_c + 1/n_m)}$ where $\bar{x}_c$ and $\bar{x}_m$ are the means for the two groups respectively, n_c and n_m are the number of stocks in each group while s^2 is the pooled standard deviation calculated as $s^2 = [(n_c - 1)s_c^2 + (n_m - 1)s_m^2]/[n_c + n_m - 2]$, where s_c^2 and s_m^2 are the standard deviation of measure for the cross and market stocks respectively. We use the SAS package to perform all tests. If the variances are significantly different, the standard approximation supplied in SAS is used. For the *Daily volatility* measure, we use an F-test to test for differences in variance between the two groups, where the null is that the ratio of the two sample variances is equal to 1.

ALL TRADES	S&P 500 Jan-July	S&P 500 stocks	Fund stocks	Crossed stocks	Market stocks	Diff. test p-value	Crossed/ Market	Diff. test p-value
Spread measures								
Effective spread	0.1151	0.1143	0.1106	0.0982	0.1201**	0.0006	0.1034	0.1157
Quoted $ spread	0.1360	0.1359	0.1374	0.1222	0.1478**	0.0021	0.1312*	0.0204
Quoted % spread (midp.)	0.3414	0.3586	0.3023[a]	0.2629	0.3197**	<.0001	0.3068**	0.0037
Volume measures								
Trades	758	772	758	890	621*	0.0255	911	0.8897
Shares traded (1000)	1073	1097	1079	1404	871**	0.0015	1181	0.2454
Volume (mill. USD)	58	57	56	76	42**	<.0001	68	0.5154
Trade size (1000 USD)	77	74	74	83	67**	0.0004	68**	<.0001
Liquidity ratios and depth								
Daily LR (mill.USD)	116.62	108.23	121.45	179.70	82.28**	<.0001	143.74	0.2189
Intraday LR (mill.USD)	12.69	11.81	12.02	17.68	8.34**	<.0001	13.92	0.1771
Depth at quotes (shares)	1851	1385	1652	1805	1601	0.2018	1596	0.2369
Volatility and return								
Daily volatility (10 day std.dev)	0.0238	0.0250	0.0261[a]	0.0241	0.0269**	<.0001	0.0266**	<.0001
Intraday volatility (15 min. % std.dev)	0.2785	0.3048	0.2847[a]	0.2960	0.2662**	0.0078	0.3128	0.2163
Average stocks per date	452	454	423	107	216		100	

a Equality of the measure between the S&P 500 and Fund stocks is rejected at the 5% level.
* Equality of the measure between the Crossed and Non-crossed stocks (Market stocks) is rejected at the 5% level.
** Equality of the measure between the Crossed and Non-crossed stocks (Market stocks) is rejected at the 1% level.

Table 4: **Time series of liquidity and activity measures over all sample stocks**

The time series of liquidity and activity measures of 40 trading days surrounding the actual trade dates for the crossed stocks (C) and non-crossed stocks (M) that were bought in the market in the portfolio. A t-test for differences in means between the two groups is performed for each date for each measure. Numbers in bold indicate a significant difference at the 5% level. The test applied is a two-sided t-test, where the null is that the mean for the "Crossed stocks" and "Market stocks" are equal. The test depends on whether the population variances of the the two groups are equal or not. If the variances are equal, then the t-stat is calculated as $t = (\bar{x}_c - \bar{x}_m)/\sqrt{s^2(1/n_c + 1/n_m)}$ where $\bar{x}_c$ and $\bar{x}_m$ are the means for the two groups respectively, n_c and n_m are the number of stocks in each group while s^2 is the pooled standard deviation calculated as $s^2 = [(n_c-1)s_c^2 + (n_m-1)s_m^2]/[n_c + n_m - 2]$, where s_c^2 and s_m^2 are the standard deviation of measure for the cross and market stocks respectively. We use the SAS package to perform all tests. If the variances are significantly different, the standard approximation supplied in SAS is used.

	Effective spread		Quoted spread (USD)		Quoted % spread		Shares traded		Volume USD		Trades		Trade size (Shares)		LR (daily)		LR Intraday		Depth (shares)		Intraday Volatility	
Date	C	M	C	M	C	M	C	M	C	M	C	M	C	M	C	M	C	M	C	M	C	M
-20	**0.0942**	**0.1142**	**0.1205**	**0.1421**	**0.2388**	**0.3093**	**1388**	**832**	**76**	**43**	**879**	**560**	**91**	**77**	**168**	**86**	**17**	**9**	1864	1724	0.2503	0.2334
-19	**0.0971**	**0.1144**	**0.1219**	**0.1404**	**0.2413**	**0.3098**	**1346**	**798**	**71**	**41**	**916**	**610**	**79**	**67**	**161**	**85**	**16**	**8**	1820	1660	0.2776	0.2721
-18	**0.0937**	**0.1151**	**0.1206**	**0.1429**	**0.2407**	**0.3115**	**1122**	**771**	**59**	**40**	781	559	78	73	**161**	**86**	**15**	**9**	1931	1634	0.2334	0.2380
-17	**0.0956**	**0.1149**	**0.1188**	**0.1408**	**0.2388**	**0.3087**	**1308**	**804**	**69**	**42**	**905**	**570**	**77**	**74**	**168**	**83**	**17**	**9**	1962	1745	0.2608	0.2433
-16	**0.0967**	**0.1163**	**0.1200**	**0.1426**	**0.2373**	**0.3089**	**1235**	**762**	**68**	**40**	**841**	**561**	**80**	**73**	**167**	**82**	**16**	**8**	1974	1654	0.2437	0.2455
-15	**0.0955**	**0.1104**	**0.1190**	**0.1363**	**0.2359**	**0.2994**	**1295**	**763**	**71**	**40**	**899**	**583**	**75**	**70**	**171**	**80**	**17**	**8**	2154	1860	0.2406	0.2307
-14	**0.0956**	**0.1161**	**0.1194**	**0.1415**	**0.2384**	**0.3086**	**1309**	**822**	**72**	**43**	853	626	**81**	**69**	**175**	**81**	**17**	**9**	**1939**	**1620**	0.2442	0.2442
-13	**0.0954**	**0.1173**	**0.1197**	**0.1445**	**0.2420**	**0.3210**	**1356**	**835**	**73**	**43**	**955**	**669**	**79**	**65**	**176**	**81**	**18**	**9**	1799	1562	0.2923	0.2817
-12	**0.0979**	**0.1165**	**0.1226**	**0.1445**	**0.2438**	**0.3198**	**1400**	**727**	**75**	**37**	**950**	**556**	**82**	**67**	**180**	**82**	**17**	**8**	1773	1567	0.2697	0.2643
-11	**0.0969**	**0.1097**	**0.1201**	**0.1369**	**0.2370**	**0.3046**	**1375**	**759**	**72**	**38**	**910**	**521**	**82**	**73**	**176**	**88**	**17**	**8**	**2094**	**1572**	0.2569	0.2424
-10	**0.0933**	**0.1137**	**0.1170**	**0.1452**	**0.2369**	**0.3167**	**1380**	**861**	**70**	**43**	886	631	**80**	**69**	**184**	**86**	**17**	**8**	**1836**	**1541**	0.2827	0.2619
-9	**0.0962**	**0.1198**	**0.1208**	**0.1493**	**0.2417**	**0.3187**	**1441**	**855**	**74**	**46**	**1002**	**641**	**78**	**71**	**189**	**86**	**17**	**9**	1771	1539	**0.2753**	**0.2485**
-8	**0.0938**	**0.1182**	**0.1184**	**0.1470**	**0.2394**	**0.3191**	**1285**	**876**	**67**	**46**	880	649	**81**	**70**	**188**	**87**	**16**	**10**	**1941**	**1545**	0.2594	0.2540
-7	**0.0936**	**0.1179**	**0.1185**	**0.1452**	**0.2373**	**0.3155**	**1324**	**862**	**68**	**43**	844	632	**83**	**68**	**191**	**84**	**17**	**8**	1950	1684	0.2555	0.2488
-6	**0.0930**	**0.1177**	**0.1167**	**0.1476**	**0.2334**	**0.3149**	**1375**	**819**	**70**	**42**	**849**	**582**	**83**	**74**	**184**	**85**	**17**	**9**	**2267**	**1756**	0.2457	0.2357
-5	**0.0946**	**0.1286**	**0.1194**	**0.1540**	**0.2277**	**0.3179**	1374	965	75	50	944	732	**76**	**68**	**204**	**98**	**20**	**10**	1879	1636	0.2413	0.2454
-4	**0.0955**	**0.1169**	**0.1206**	**0.1479**	**0.2363**	**0.3159**	**1291**	**846**	**67**	**41**	860	617	**76**	**65**	**185**	**89**	**16**	**8**	**1953**	**1618**	0.2477	0.2427
-3	**0.0950**	**0.1159**	**0.1184**	**0.1439**	**0.2337**	**0.3069**	**1239**	**874**	**66**	**42**	819	627	**81**	**68**	**182**	**90**	**15**	**8**	1858	1594	0.2717	0.2550
-2	**0.0963**	**0.1149**	**0.1196**	**0.1421**	**0.2367**	**0.3085**	**1499**	**806**	**76**	**39**	**948**	**562**	**81**	**69**	**176**	**88**	**17**	**7**	**2074**	**1668**	0.2833	0.2674
-1	**0.0968**	**0.1215**	**0.1197**	**0.1446**	**0.2373**	**0.3147**	**1231**	**779**	**66**	**38**	**854**	**570**	**77**	**67**	**173**	**86**	**16**	**8**	**1955**	**1629**	0.2806	0.2720
0	**0.0982**	**0.1201**	**0.1222**	**0.1478**	**0.2629**	**0.3197**	**1404**	**871**	**76**	**42**	**890**	**621**	**83**	**67**	**180**	**82**	**18**	**8**	1805	1601	**0.2960**	**0.2662**
1	**0.0958**	**0.1170**	**0.1217**	**0.1461**	**0.2435**	**0.3163**	**1405**	**824**	**76**	**41**	**877**	**602**	**84**	**68**	**177**	**84**	**19**	**8**	1866	1563	0.2757	0.2548
2	**0.0915**	**0.1129**	**0.1139**	**0.1392**	**0.2266**	**0.3036**	**1291**	**858**	**71**	**43**	**837**	**613**	**83**	**70**	**179**	**84**	**17**	**9**	**2115**	**1647**	0.2747	0.2564
3	**0.0925**	**0.1112**	**0.1166**	**0.1388**	**0.2318**	**0.3030**	**1443**	**917**	**83**	**44**	**828**	**606**	**93**	**74**	**183**	**84**	**20**	**9**	**2078**	**1597**	0.2591	0.2546
4	**0.0956**	**0.1128**	**0.1180**	**0.1387**	**0.2371**	**0.3035**	**1441**	**842**	**80**	**41**	**898**	**554**	**94**	**73**	**186**	**87**	**18**	**8**	**1983**	**1596**	**0.2720**	**0.2470**
5	**0.0903**	**0.1116**	**0.1158**	**0.1392**	**0.2318**	**0.3036**	**1258**	**795**	**69**	**39**	**871**	**596**	**78**	**65**	**188**	**88**	**18**	**8**	1883	1582	0.2374	0.2446
6	**0.0947**	**0.1119**	**0.1194**	**0.1404**	**0.2362**	**0.3024**	**1511**	**946**	**84**	**48**	**971**	**671**	**87**	**72**	**189**	**87**	**21**	**10**	1799	1545	0.2647	0.2662
7	**0.0953**	**0.1132**	**0.1196**	**0.1412**	**0.2364**	**0.3065**	**1310**	**874**	**72**	**45**	842	626	**83**	**70**	**190**	**88**	**17**	**9**	**1938**	**1541**	0.2726	0.2604
8	**0.0970**	**0.1173**	**0.1220**	**0.1462**	**0.2399**	**0.3134**	**1311**	**869**	**75**	**44**	**848**	**629**	**86**	**69**	**189**	**85**	**17**	**9**	1741	1576	0.2862	0.2797
9	**0.0949**	**0.1146**	**0.1205**	**0.1480**	**0.2382**	**0.3204**	**1047**	**641**	**58**	**32**	**745**	**455**	**76**	**69**	**188**	**88**	**16**	**7**	1747	1514	0.2463	0.2351
10	**0.0941**	**0.1181**	**0.1153**	**0.1423**	**0.2291**	**0.3030**	**1299**	**804**	**74**	**40**	**853**	**559**	**82**	**72**	**191**	**89**	**18**	**8**	**1987**	**1557**	0.2656	0.2644
11	**0.0979**	**0.1182**	**0.1206**	**0.1447**	**0.2387**	**0.3076**	**1547**	**920**	**84**	**46**	**905**	**587**	**94**	**77**	**185**	**89**	**19**	**9**	1839	1588	0.2783	0.2731
12	**0.0959**	**0.1162**	**0.1183**	**0.1436**	**0.2346**	**0.3049**	**1521**	**889**	**84**	**44**	**987**	**636**	**85**	**71**	**183**	**92**	**20**	**8**	**1975**	**1592**	0.2622	0.2684
13	**0.0929**	**0.1162**	**0.1191**	**0.1415**	**0.2420**	**0.3094**	**1416**	**730**	**80**	**38**	**978**	**532**	**80**	**72**	**182**	**103**	**20**	**9**	**1718**	**1479**	0.2525	0.2626
14	**0.0950**	**0.1156**	**0.1193**	**0.1470**	**0.2364**	**0.3106**	**1395**	**852**	**80**	**44**	**968**	**625**	**80**	**70**	**172**	**92**	**18**	**10**	**1932**	**1523**	0.2532	0.2630
15	**0.0966**	**0.1190**	**0.1203**	**0.1460**	**0.2414**	**0.3083**	**1665**	**974**	**89**	**49**	**1084**	**696**	**81**	**71**	**166**	**95**	**20**	**10**	**1877**	**1550**	0.2983	0.2757
16	**0.0955**	**0.1165**	**0.1197**	**0.1464**	**0.2428**	**0.3142**	**1429**	**920**	**79**	**48**	**963**	**666**	**79**	**71**	**171**	**96**	**18**	**9**	**1870**	**1541**	0.2969	0.2791
17	**0.0939**	**0.1199**	**0.1203**	**0.1495**	**0.2430**	**0.3208**	**1232**	**806**	**68**	**43**	**844**	**592**	**79**	**72**	**171**	**94**	**16**	**10**	1853	1549	0.2318	0.2382
18	**0.0955**	**0.1221**	**0.1193**	**0.1523**	**0.2419**	**0.3181**	**1252**	**790**	**72**	**44**	**896**	**652**	**76**	**67**	**168**	**93**	**17**	**10**	1967	1656	0.2748	0.2659
19	**0.0920**	**0.1181**	**0.1169**	**0.1451**	**0.2372**	**0.3075**	**1387**	**925**	**81**	**53**	920	723	**87**	**73**	**166**	**93**	**20**	**12**	1987	1623	0.2761	0.2748
20	**0.0953**	**0.1200**	**0.1198**	**0.1498**	**0.2421**	**0.3139**	1466	1130	**84**	**59**	953	839	**86**	**71**	**178**	**100**	**19**	**11**	**1880**	**1528**	0.3012	0.3047
All dates	**0.0951**	**0.1164**	**0.1193**	**0.1442**	**0.2382**	**0.3112**	**1356**	**844**	**74**	**43**	**896**	**613**	**82**	**70**	**179**	**88**	**18**	**9**	**1918**	**1604**	0.2656	0.2576

Table 5: **Probit model estimating determinants of probability of a cross**

We estimate a probit model of the probability that a given order is successfully crossed. The probability of observing a cross is assumed to be given by the model

$$y = Pr\,(\text{cross}) = F\,(\beta_0 + \beta_1 \text{eff\_spread}_i + \beta_2 \text{depth}_i + \beta_3 \text{LR}_i + \beta_4 \text{volume}_i + \beta_5 \text{vola}_i + \epsilon_i)$$

where $F(\cdot)$ is the cumulative normal distribution function, and the β's are coefficients of the explanatory variables. Explanatory variables include the effective spread ("eff_spread"), the average depth at the inner quotes ("depth"), the intraday liquidity ratio ("LR"), the trading volume measured in USD ("volume"), and the standard deviation of daily returns measured over the last 10 days ("' vola"). The total data set contains 646 transactions, of which 214 were crosses. The intraday liquidity variable is highly correlated with the dollar volume of trading. We therefore use orthogonal versions of these two variables in the regression model. $\frac{dy}{dx}$ is the slope estimates (marginal effects) at the means of the regressors. These estimates predict the effects of changes in one of the explanatory variables on the probability of belonging to a certain trade category.

	coefficient	std deviation	pvalue	dy/dx
β_0: constant	0.0888	0.1887	0.6380	
β_1: eff_spread	-4.8483	1.4834	0.0010	-1.7173
β_2: depth	-0.0002	0.0314	0.9940	-0.0001
β_3: LR	0.1926	0.0528	0.0000	0.0682
β_4: volume	0.2424	0.5630	0.0000	0.0858
β_5: vola	-1.4638	3.3163	0.6590	-0.5185
n	646.0000			
Wald $\chi^2(5)$	27.9400			
Prob > χ^2	0.0000			
Log likelihood	-389.0788			
pseudo R^2	0.0516			
Observed P	0.3313			
Predicted P (at means)	0.3129			

Table 6: **Decomposition of the implicit costs for the opportunistic crossing strategy**

Estimates of the average implicit costs for the opportunistic crossing strategy are decomposed into (i) the average implicit cost *excluding* the costs associated with the delay of orders, (ii) the average delay cost, and (iii) the average implicit cost *including* the delay cost, i.e. the average implicit implementation shortfall cost. The two last columns show respectively the number of trading days and the number of stocks traded for each type of orders.

Average implicit costs	Costs ex delay	Delay costs	Impl. shortfall	Days	Stocks
All orders	0.088	-0.121	-0.033	16	4 517
Crossed orders	0.055	0.056	0.111	15	3 767
Non-crossed orders	0.254	-0.998	-0.744	3	750
Delayed orders:					
All delayed orders	0.018	-0.620	-0.603	3	865
Delayed crossed orders	-0.415	0.465	0.049	2	447
Delayed non-crossed orders	0.483	-1.787	-1.304	1	418

Table 7: **Estimates of implicit costs for different trading strategies - pre-trade benchmark**
The table shows the execution cost estimates for four alternative submission strategies in addition to the original strategy (*Opportunistic Cross*). The estimates are based on the implementation shortfall methodology. The second strategy in the table, *Pure cross*, is the result of a hypothetical strategy where we assume that the entire residual order would have been crossed in equal amounts over the 10 days after the decision to trade. We split the non-crossed part of the order into 10 equal orders, each one of which is assumed crossed at the closing price each of the 10 days. The three last strategies in the table show the implicit cost estimates for the three submission strategies in the primary market. The first limit order strategy (LO1) is the most passive strategy which assumes that limit orders are submitted at the opening bid ("At-the-quote" limit order strategy), ignoring order sizes (no sub orders) as in Handa and Schwartz (1996). Whenever we observe a trade at our limit price or better, we assume the entire order is filled at that price. The second limit order strategy (LO2) assumes that limit orders are submitted sequentially at the prevailing bid following the filling of a suborder ("chasing the market"). However, in this case we ignore the size of each suborder. The third limit order strategy (LO3) is the most realistic strategy where all limit orders (also suborders) are submitted sequentially at the prevailing bid following the filling of a suborder as for LO2, but this simulation also takes the size of each suborder into account when evaluating the fill. If we observe a trade that is larger or equal in size to our order, we assume that our order would have been filled at that price. If there is a fill, the next suborder is submitted at the following bid. For all strategies, we assume that the remaining/unfilled part of an order is bought at the opening price the next day. Numbers in bold are estimates that are significantly different from zero at the 1% level. For each strategy and original group of stocks, tests of difference in means between the original submission strategy and the respective strategies are performed where ** indicates a significant difference in implicit costs at the 1% level.

Implicit costs	Opport. Cross	Pure Cross	LO 1	LO 2	LO 3
EW					
All orders	**0.0879**	**0.1443**	**0.0626**	**0.1303**	**0.2435****
Crossed orders	0.0553	0.0553	-0.0147**	**0.0520**	**0.1729****
Non-crossed orders	**0.2536**	**0.5867**	**0.4317****	**0.5048****	**0.6143****
VW					
All orders	0.2028	0.2534	0.0836	0.2849	0.3885
Crossed orders	0.1837	0.1837	0.0141	0.2007	0.3025
Non-crossed orders	0.3101	0.5867	0.4298	0.6615	0.7892

Table 8: **Fill rates and order execution time for different trading strategies**

Panel (a) shows the fill rates for the different strategies with respect to the total number of shares and the number of orders filled. Panel (b) shows the fill rates across the groups of crossed/non-crossed stocks. Panel (c) shows the average execution time (in minutes) for the entire strategy with respect to the opening time of the market (minutes since open). The numbers in parenthesis are the average execution time of the orders (minutes since submission). For the opportunistic and pure crossing strategies these numbers are ignored since they are over several days. For LO1, the measure of "minutes since open" and "minutes since submission" is equal because only one order is submitted for each stock.

(a) Fill rates for submission strategies

	Opport. Cross	Pure Cross	LO1	LO2	LO3
Orders					
Filled (%)	83.2%	100.0%	85.6%	71.9%	65.1%
Not filled (%)	16.8%	0.0%	14.4%	28.1%	34.9%
Submitted orders	3909	3909	3909	11864	11289
Filled orders	3316	3909	3346	8528	7347
Unfilled orders	594	0	563	3336	3942
Shares					
Filled (%)	84.8%	100.0%	88.5%	49.7%	42.5%
Not filled (%)	15.2%	0.0%	11.5%	50.3%	57.5%
Shares in submitted orders	26776710	26776710	26776710	26776710	26776710
Shares in filled orders	22714683	26776710	23693158	13303893	11372729
Shares in unfilled orders	4070060	0	3083552	13472817	15403981

(b) Fill rates across groups

	Opport. Cross	Pure Cross	LO1	LO2	LO3
Orders					
Cross group:					
Filled (%)	83.2%	100.0%	84.8%	70.9%	64.0%
Not filled (%)	16.8%	0.0%	15.2%	29.1%	36.0%
Non-crossed group:					
Filled (%)	100%	-	89.7%	76.3%	70.2%
Not filled (%)	0	-	10.3%	23.7%	29.9%
Shares					
Cross group:					
Filled (%)	84.8%	100.0%	88.1%	48.9%	41.5%
Not filled (%)	15.2%	0.0%	11.9%	51.1%	58.5%
Non-crossed group:					
Filled (%)	100%	-	90.5%	53.6%	47.7%
Not-filled (%)	0	-	9.6%	46.4%	52.3%

(c) Execution time (minutes)

	Opport. Cross	Pure Cross	LO1	LO2	LO3
Mean	-	-	30 (30)	42 (22)	71 (38)
Median	-	-	7 (7)	9 (5)	24 (10)
Minimum	-	-	0 (0)	0 (0)	0 (0)
Maximum	-	-	389 (389)	390 (390)	390 (390)
First quartile	-	-	3 (3)	4 (1)	7 (1)
Third quartile	-	-	19 (19)	31 (14)	80 (34)
Standard deviation	-	-	67 (67)	80 (56)	102 (73)

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