Equity Trading by Institutional Investors: To Cross or Not to Cross? [★]

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Abstract

The proliferation of market places and trading methods is a striking feature of current equity markets. A stated goal of all the new trading arrangements is to reduce transactions costs. We investigate costs in one new market place, the crossing network. A crossing network is a satellite trading place; it uses prices derived from a primary market, and merely matches on quantity. Using a data sample from a large institutional investor, we provide evidence that low measured costs in crossing networks are offset by substantial costs of trading failures. The costs of trading failures due to adverse selection in the network's order execution, are not reflected in standard measures of transactions costs.

Key words: Costs of equity trading, Trading mechanisms, Alternative trading systems, Crossing networks, Institutional equity trading.

Advances in electronic communication technology, intensified competition between market centers, and a need to handle increasingly high trading volumes

have resulted in a proliferation of market places and trading methods in the US equity market. The consequences of this development for the main functions of the market are complex and not yet well understood.

A stated goal of all new trading arrangements is to reduce transactions costs. Current academic research on the costs of equity trading (e.g., Conrad et al. (2003)) shows a distinct cost advantage to alternative trading systems, such as ECNs and crossing networks, over exchange-based trading (NYSE and/or NASDAQ). In fact, the magnitude of the cost differences leads Conrad et al. (2003) to question whether these are sustainable as equilibria. If alternative trading systems are so cheap, why isn't everybody using them? The prime aim of this paper is to shed some light on this issue. By analyzing a trading strategy which involves extensive use of crossing, we find evidence that the low costs associated with this trading method are offset by substantial adverse selection costs. This possibility is in fact pointed out by Conrad et al. (2003) as an issue not accounted for in their analysis. Our analysis also shows how the standard method of measuring costs conceals this cost component.

The costs associated with trading failures (non-trading) are notoriously hard to measure. Ever since the introduction by Treynor (1981) and Perold (1988) of the concept of *implementation shortfall* into the literature on the cost of equity trading, trading failure or trading delay has been acknowledged as a potential cost factor. However, there are few empirical studies of this issue. In their survey of the work on institutional trading costs, Keim and Madhavan (1998) argue that this is primarily due to data limitations.

A crossing network is a satellite market, coexistent with and dependent on another marketplace such as the NYSE or NASDAQ. Participants submit desired buy or sell quantities, which are then matched at a prearranged price, for example, the closing price at the next close. A crossing network is suitable for a study of non-trading costs for two reasons: first, there is a nontrivial risk of not filling orders, and second, the crossing network does not have any separate price discovery. In markets with price discovery, adverse selection is one of the causes of price movements, but in the crossing network, where price is fixed elsewhere, *execution probability* is the only thing that can be affected by adverse selection. Special features of the investor's trading strategy and the fact that we have detailed information about the strategy ex ante allow us to make statements about the non-trading costs of crossing. [1]

The intuition for our main result is simple. Suppose an investor has decided to submit a buy order for one share of IBM to the crossing network. The crossing network guarantees the investor today's closing price if a counterpart is found who is willing to sell the IBM share. If not, the investor experiences a trading

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[1] In other studies, including Conrad et al. (2003), information about the trading strategy has to be inferred from the sequence of orders.

failure. The cost of this trading failure has two components. One component is that the investor's portfolio does not contain IBM. This cost depends on the investor's motivation for wanting to add IBM to his or her portfolio, and it is hard to say much about this cost in general. The other component is the delay component. Suppose that in the case of a trading failure, the investor submits a market order to buy one share of IBM to NYSE the following day. The market price for IBM will then most likely have moved from yesterday's closing price. This difference between the price paid and yesterday's closing price is the *delay cost*. If the price of IBM is as likely to go up as down, the delay cost has expectation zero. However, if trading failures in the crossing network are adversely selected, delay costs will tend to be positive for the unbought stocks you do not get and negative for the stocks that were bought. To see this, let us expand on the example, and let the investor instead submit buy orders for two stocks, IBM and Apple, to the crossing network. Further suppose that some investors are informed that IBM is underpriced and Apple is overpriced. Adverse selection will have two effects: (i) the likelihood of obtaining IBM is lower than the likelihood of obtaining Apple, and (ii) the price of IBM will most likely go up tomorrow while the price of Apple will most likely go down. Thus, due to adverse selection in the timing of order execution, the investor gets both stocks at an unfavorable price (Apple early and IBM late). This is what we show. The stocks an investor *acquires* in a crossing network have a low (or negative) delay cost, and the stocks the investor *does not acquire* have a high delay cost.

The structure of the paper is as follows. We start by giving a short overview of the relevant literature. In section 2 we provide some details about the data sample, including the trading strategy. Section 3 compares measured trading costs in the two marketplaces: crossing networks and traditional exchanges. Section 4 focuses on the issue of adverse selection and the cost of non-trading, and section 5 offers some concluding remarks.

1 Literature

This paper relates to two strands of the market microstructure literature. One is the literature on the cost of equity trading. The other is the literature on competing marketplaces and the effects of different competitive environments on welfare.

1.1 Trading costs

The literature on trading costs focuses on the measurement problem: what is the cost of establishing or changing an equity position? Using the classification of Keim and Madhavan (1998), total trading costs can be split into explicit and implicit costs of trading,

$$\text{Total cost} = \underbrace{\text{Broker commissions}}_{\text{Explicit Cost}} + \underbrace{\text{Spread} + \text{Price impact} + \text{Opportunity cost}}_{\text{Implicit Cost}} \quad (1)$$

The explicit costs are the actual out-of-pocket costs of trading, such as brokers' fees. [2] The implicit costs consist of spread costs, price impact costs and opportunity costs. In a dealer market, the spread is set to cover the specialists' costs of market making. [3] Prices may at times have to move away from the bid-ask spread to enable an order to be executed. The resulting price impact cost may be decomposed into a temporary component reflecting the liquidity cost of the trade, and a permanent component reflecting possible new information. Opportunity costs include all costs related to unexecuted orders (non-trading costs). Spread costs, information costs, and opportunity costs are all related to the adverse selection problem studied in most of the theoretical market microstructure literature. There is always a risk that a given order is informed, and this risk is presumably greater for large orders.

A theoretically correct computation of the total cost of a trade would require the price of the stock in the case where the trade did not take place. As a substitute for this unobservable "unperturbed" price, the current literature has settled on the price observed at the time the *decision* to trade was made. This "implementation shortfall" approach was pioneered by Perold (1988) and Wagner and Edwards (1993), and is applied to institutional orders in the US markets in Keim and Madhavan (1995), Chan and Lakonishok (1995), Keim and Madhavan (1997), and Jones and Lipson (1999).

The early literature on trading costs focuses on the main markets (NYSE and NASDAQ). A central finding is that implicit trading costs are much larger than explicit trading costs. The literature also concludes that trading costs vary by such factors as trading strategy, order size and firm size. There is also some recent work on trading costs in alternative trading systems. Of particular

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[2] In a study by Keim and Madhavan (1997), the reported average commission is 0.2% of trade value. Jones (2000) provides evidence of a significant lowering of commissions in the US equity markets over the last decade.
[3] The spread from a limit order book reflects the difference in limit prices among different traders. Cohen et al. (1981) develop a model of the bid-ask spread in a market with many competing limit order traders.

relevance to our paper are Conrad et al. (2003), who find that alternative trading systems, such as ECNs and crossing networks, have a distinct cost advantage compared with regular exchanges.

1.2 Multiple marketplaces

The most important question in the academic literature on intermarket competition is whether competition between marketplaces induces efficient trading.

The survey by Biais et al. (2005) divides the existing literature into two generations depending on the assumed nature of competition between dealers and market makers. The first generation assumes a fully competitive environment, while the second relaxes this assumption and discusses cases in which liquidity is provided by strategic agents who exploit some form of market power. In the case of competitive liquidity supply, Chowdhry and Nanda (1991) argued for a tendency towards the "winner takes most" type of outcome. Both informed traders and liquidity traders will flock to the largest exchange, informed traders because the bigger the liquidity order flow, the easier it is to "hide," and liquidity traders because the more *other* liquidity traders that are present, the lower their costs. Research within the second generation points to the benefits of allowing investors to compete to supply liquidity themselves. In the case where strategic liquidity suppliers have some form of market power, they may find it optimal to provide liquidity outside the primary market.[4] Lipson (2003) examines empirically the competition among several market centers for NYSE-listed stocks. In summarizing his results he writes "..*competition for execution services in NYSE-listed stocks is characterized more by fragmentation and specialization than the introduction of universally better market design.*"

Crossing networks have been around since the late 1960s.[5] Until recently, however, they have not presented serious competition to the traditional bastions of trading. A major impetus for the growth of trading through such networks has been the growth of institutional investors, and the need of these investors to obtain large quantities of equities, for example for index tracking purposes. Participants in a crossing network submit unpriced orders to buy or sell given quantities. Quantities are then matched in the cross. There is an ex ante agreement that the price in the cross will be some contractible, observable price determined outside the crossing network. Examples are the use of the closing price on the NYSE or NASDAQ on the day of the cross, or a weighted average of prices during the trading day. Note that the crossing

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[4] See Biais et al. (2005), section 3.
[5] A good source for institutional details about crossing networks is Harris (2003), in particular the discussion on pages 132–134.

price is not observable at the time of order submission. The participants in the cross "agree not to disagree" about the price at which the given quantities are matched. When an order is submitted to a crossing network, there is therefore uncertainty both as to whether the order will be filled and, if it is, at what price.

Several trading cost components are low for traders in crossing networks compared with trading on regular exchanges. First, crossing commissions are substantially lower than commissions charged by brokers on exchanges. Second, there are no spread costs because the participants in the network are providing the liquidity themselves. Finally, there are no direct price impact costs because the price is set independently of order size. There may, however, be an "implicit" price impact if the existence of a large crossing order is known to participants in the primary market. There is also an implicit price impact due to the removal of crossing orders from the primary market, which may affect primary market prices. The risk of non-execution suggests that both timing costs and opportunity costs due to failure to execute may be significant. Moreover, the anonymity provided by most networks makes crossing attractive to informed traders. Uninformed liquidity traders who use crossing networks to reduce explicit and implicit trading costs might therefore incur costs related to adverse selection.

The particular competitive environment of a main market and a satellite crossing market has raised some specific concerns. A reduction in primary market liquidity could harm all market participants. In addition, because crossing networks do not compensate the primary market for the use of their price discovery process, the environment may represent unfair competition. Some support for this view can be found in Mendelson (1987). Mendelson argues that market fragmentation has both costs (in the form of low liquidity and high volatility) and benefits (in the form of better 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 as a result of low liquidity and high volatility remain. These arguments are supported by models emphasizing asymmetric information, such as Easley et al. (1996), who argue that off-market trading is driven by "cream skimming" of orders originating from uninformed traders, and is most common for small orders in liquid securities. By contrast, reputation models such as Seppi (1990) explain the benefits of trading outside exchanges in terms of the ability to screen out informed investors and permit mutually advantageous trades off-market. If this is the case, trading outside exchanges will be largely complementary to exchange trading, and off-market trading will be more likely for large orders, especially in less liquid stocks.

Fong et al. (1999) find support for an asymmetric information explanation: off-market trading in the Australian stock market is driven by institutional

trading interest and liquidity. Conrad et al. (2003) find similar results for both the NYSE and the NASDAQ: alternative trading systems do provide significant competition for order flows from institutional investors. On the other hand, Gresse (2002) finds no indication that the relative trading volume in a crossing network has adverse effects on primary market spreads. Moreover, in a study of the price impact cost of block trades across a primary market, an upstairs market, and a crossing network, Fong et al. (2003) report that there is no evidence of adverse effects in the primary market due to competition from the other trading venues.

The specific case of a crossing system has received relatively little focus in the theoretical literature. A notable exception is Hendershott and Mendelson (2000), who look at the coexistence of exchanges and crossing networks. They show that there are subtle interactions between the two markets, and that the presence of a crossing network may have negative effects on the underlying market, in particular if the market is used as a "dealer of last resort." Other papers discussing crossing networks include Dönges and Heinemann (2001) and Degryse et al. (2003).

1.3   This study

Our paper addresses cost measurement in a setting where cost estimates can be correctly conditioned on the trader's choice of marketplace.

A comparison of transactions costs should always be conditioned on the trader's submission strategy. This is because orders may be routed in a particular way based on an initial conception of how hard it will be to fill them. In the case of a single market, traders make a choice with respect to order type, i.e., market orders or limit orders. In the case of multiple trading venues, traders also decide which market to use. Suppose a trader follows a submission strategy in which all orders perceived to be difficult to fill are submitted to the exchange, and all remaining orders are submitted to a crossing network. Transaction data from the trades of this trader would most likely show the highest transactions costs at the stock exchange, yet this is not necessarily due to the inherent properties of the exchange, but rather to the particular submission strategy followed by the trader.[6]

In our data set, the submission strategy is known and set in advance. The

[6] Conrad et al. (2003) try to control for this selectivity bias in their cost comparison across exchanges by means of a binary choice analysis. Here, measures of trade difficulty are assumed to affect the submission strategy, and the submission strategy is estimated. Similar methods are used in studies of choices between upstairs and downstairs trading on the NYSE, such as Keim and Madhavan (1996).

submission strategy is called "opportunistic crossing." Initially, all orders are submitted to a crossing network. Any order which is not filled in the crossing network by the end of the trading day is sent on to the main market.[7] We know that the market on which the stocks are actually traded is a function of factors external to the submission strategy, and this allows us to make stronger statements about market reactions. Consider equation (2), which gives a unifying framework for the analysis in this paper.

$$E[\text{Trading cost}] = p(\text{cross})E\left[\text{cost}|\text{cross}\right] + (1 - p(\text{cross}))E\left[\text{cost}|\text{no cross}, \text{market}\right] \quad (2)$$

We write the expected trading cost in two parts. $E[\text{cost}|\text{cross}]$ is the expected trading cost conditional on the order being crossed, $E[\text{cost}|\text{no cross, market}]$ is the expected trading cost conditional on the order not being crossed and then subsequently traded in the market, and $p(\text{cross})$ is the probability that an order submitted first to a crossing network is crossed.

Writing the expected costs as in equation (2) facilitates comparisons with other studies of trading costs. Cost comparisons across marketplaces are based on estimates of $E[\text{cost}|\cdot]$ for the various markets. However, the conditioning information may not be the same in different studies, for instance because of variations in traders' submission strategies. This fact is not always acknowledged in studies which compare costs across markets.

Our focus is on $p(\text{cross})$, the probability of an order being traded in the crossing network. Our main contribution is to show that this probability is affected by information. Because the Government Petroleum Fund used the market as a "dealer of last resort," we know the identity of stocks that were initially attempted crossed but which subsequently had to be acquired in the open market. This particular type of information enables us to look for signs of adverse selection in the crossing network.

Our result is important because it shows the mechanism by which two different markets can be made to coexist. Existing empirical evidence suggests that measured trading costs for crossing networks are significantly lower than trading costs in a main market like the NYSE. From an equilibrium point of view, this result is intriguing because it indicates that most traders should gravitate towards a trading strategy of submitting to crossing networks. Our results show that the mechanism which can offset this effect is adverse selection of order execution in the crossing networks.

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[7] This strategy is shown to be optimal behavior for certain types of traders in Hendershott and Mendelson (2000).

2 The data

The data set we use was provided by the Norwegian Government Petroleum Fund (hereafter the Fund). The Fund, which was established in 1990, is a vehicle for investing the Norwegian Government's income from petroleum-related activities in international capital markets. In 1998, the Fund was for the first time allowed to invest in equity instruments, with a target equity percentage of 40 percent. Equities were phased in gradually during the first half of 1998. By the end of June 1998, the market value of the total Petroleum Fund portfolio was $17.7 billion, and the market value of the equity portfolio was $7.2 billion. Our data set is from this build-up period, when the Fund was a large buyer of equities.

We use data for US equity markets only. Focusing on the US portion of the portfolio allows us to compare with other studies, most of which use US data. US stocks represent 28.5 percent of the Fund's benchmark for the total equity portfolio. The US portion of the FT/S&P's Actuaries World Index currently consists of slightly more than 500 different stocks, representing the largest companies on the exchange. The index is thus slightly broader-based than, but has a very high correlation with, the S&P 500 index.

The Fund did not take any active positions during the transition period. It tracked the FT/S&P's Actuaries World Index subject to a maximum tracking error. At the beginning of each month, the benchmark index was changed to allow for a prescribed increase in the equity portion of the total portfolio at the end of the month. This meant that the Fund had to buy most of the stocks in the index each month in order to comply with the upper limit for tracking error. At the end of the six month period, the Fund had a goal of a close match with the index. Towards the end the Fund thus had little "leeway" as to which stocks they needed to acquire.

Four index managers were hired to establish the equity portfolio. One of the index managers was chosen as "transition manager." The transition manager tried first to cross the Fund's desired orders internally with its own customers (internal cross). If it was impossible to find a seller in this network, the manager tried to find a seller in the customer bases of the three other index managers or sent the order to an external crossing network (external cross). If it was not possible to cross the order at all, the stock was bought in the primary market.[8] According to Ruyter (1999), this strategy is typical for relatively

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[8] The submission strategy was explained to us in meetings with those responsible for the transition in the Fund. The process of selecting managers is discussed in some detail in the Fund's 1998 annual report. The Fund used Barclays Global Investors (BGI) as transition manager. Gartmore Investment Management, Bankers Trust Company and State Street Global Advisors UK were the other three managers.

patient customers of large index managers. In the six-month period considered in the paper, the Fund was not using stock index futures when making equity transitions.

Transactions costs should be measured against the date when the decision to trade was made. Hence, the timing of the Fund's trades is important. All orders were executed within two days after the decision to trade. Eighteen percent of the investment amount was executed on the second day after the decision date, of which ten percent represented market trades. Table 1 summarizes the magnitude and actual sequence of trades by the Fund. The portfolio was established in the period from January to June 1998.[9] The total portfolio investment was $1.75 billion, of which $1.50 billion, or nearly 86 percent, was crossed. The majority of the crossed orders, $1.36 billion, was executed internally. The Fund crossed externally on two occasions, while market trades to complete the desired portfolio were needed on three trading dates.[10] The highest trading volume on one date amounted to $300 million, or 17.1 percent 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 or 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.[11]

In addition to the actual trades by the Fund, we use market data. The NYSE Trades and Quotes (TAQ) database provides trading volumes and prices. Datastream is the source of data on (longer-term) stock returns and market capitalization.[12] Table 2 shows some descriptive statistics for the trades

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According to Harris (2003), BGI's internal crossing network is "probably the largest in the world;" hence, both the manager and the private network, where most of the actual crossing was performed, are representative of the US market.

[9] The table shows that market trades sometimes happened on the same date as internal crosses. According to the order submission strategy, these orders were to be sent for external crossing before they were sent to the market. We do not know how this was done. Hence, it might be that the submission strategy was not strictly followed on this occasion. For reasons of anonymity we do not show the actual dates, but the dates are in chronological order. Some of the dates are close in time: day 3 is the day after day 2, day 6 is the day after day 5 and day 16 is the day after day 15.

[10] We do not know how aggressively the market orders were traded in the market nor the actual intraday timing of the executions.

[11] The switch to VWAP was made because the Fund was afraid that closing prices sometimes were pushed up by sellers reversing short positions in the futures markets at the end of the trading day. Our results are robust across these two sub-samples.

[12] We exclude stocks that split around the Fund's trades. In a small number of cases we are unable to match the trades with market data. The problems stem

Table 1 Establishing the US stock portfolio

The table shows the characteristics of the actual orders for the Fund during the six-month period January to June 1998. Trades were conducted on a total of 16 distinct dates. For each date we list the total dollar value of the trades (in millions of dollars) and the number of distinct securities traded (n), split up by the three types of execution: internal cross, external cross and market. Internal crosses are crosses performed with the transition manager's other customers. External crosses are trades performed with the other three institution's customers. Market trades are performed in the market, which is the NYSE or NASDAQ. The final column lists what percentage of the Fund's total trades was performed on the given date.

| date | Crosses | | | | Market | | All | | |
| | Internal | | External | | | | | | |
	mkt val	n	mkt val	n	mkt val	n	mkt val	n	Percent
1	174	454					174	454	10
2	184	453					184	453	11
3			115	342			115	342	7
4	58	153			3	29	61	182	4
5	19	65					19	65	1
6			30	105			30	105	2
7	163	130			73	303	236	433	14
8	300	634					300	634	17
9	14	88					14	88	1
10	14	49					14	49	1
11	231	465					231	465	13
12	70	386					70	386	4
13	8	45					8	45	0
14	23	48					23	48	1
15	97	350					97	350	6
16					174	418	174	418	10
	1356	3320	145	447	250	750	1751	4517	
Percent	77		8		14				

in our sample.

The Fund's trades are relatively large. The mean order is for 6851 shares with a value of $377,000. This is further confirmed by two other statistics in the

from the different identifiers used for equities in the various databases, as well as from Datastream's removing delisted companies. Except for one date, the match percentage is in the range 82-94 percent.

Table 2 Descriptive Statistics for the Fund's trades

The table provides descriptive statistics for the Fund's trades in the period January to June 1998. We provide means, standard deviations and medians split up by crosses, market orders and all trades. *Number of Shares* is the number of shares in an order. *Trade value* is the dollar value (in thousands of $) of each trade. *Fraction of company* is the size of the order relative to the total value of the company (in percent). *Fraction of primary market volume* is the size of the order relative to the total volume traded in the primary market (NYSE/NASDAQ) the same day (in percent). The total volume traded in the primary market includes the Fund's trades. *Company Market value* is the company market value (in billions of $) and *Price* is the price of the stock. The last row lists the total number of observations in each category.

	Crosses			Market			All trades		
	mean	(std)	med	mean	(std)	med	mean	(std)	med
Number of shares	7021	(9636)	3900	5920	(9108)	3400	6851	(9564)	3800
Trade value (thousands)	390	(686)	177	304	(641)	149	377	(680)	173
Fraction of company (%)	0.03	(0.02)	0.03	0.03	(0.02)	0.03	0.03	(0.02)	0.03
Fraction of primary market volume (%)	1.3	(2.7)	0.8	2.0	(3.4)	1.1	1.4	(2.8)	0.9
Company market value (bill $)	18	(29)	8	13	(26)	6	17	(29)	8
Price	53	(30)	49	51	(32)	46	53	(30)	48
Number of observations	2929			537			3466		

table. The average order is for 0.03 percent of a company's value, and 1.4 percent of the total NYSE volume that day. These orders are larger than in most other studies empirically investigating institutional trading costs.

3 Trading costs

In this section, we estimate trading costs in the two marketplaces: crossing networks and traditional exchanges. Ideally, we would like to compare the opportunistic crossing strategy with a strategy where all orders were submitted directly to the primary market. However, we can not observe the costs of following an alternative strategy.[13] Referring back to equation (2), what we observe are the two cost components $E[\text{cost}|\text{cross}]$ and $E[\text{cost}|\text{no cross, market}]$.

We estimate the Fund's trading costs following the empirical version of the implementation shortfall approach used in Keim and Madhavan (1998) and Conrad et al. (2003). This facilitates a comparison of the estimated trading costs of the Fund with estimated average trading costs from large samples of institutional investors. We estimate transactions costs as

$$\text{TC} = \text{Implicit Costs} + \text{Explicit Costs} = (P^a/P_d - 1) + C/P_d,$$

where TC is the total trading cost measured relative to the share price, C is

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[13] Using the same data set, Næs and Skjeltorp (2003) compare different trading strategies by means of a simulation analysis. Simulations of alternative trading strategies indicate that opportunistic crossing was quite cost effective.

the commission per share, P^a is the average price, and P_d is the closing price of the stock on the day before the order submission. The results are summarized in table 3.

Table 3 Average trading costs for the Fund's transactions

Average trading costs for the Norwegian Government Petroleum Fund's transactions, January to June 1998. Costs are measured as in Keim and Madhavan (1998): Implicit trading costs are defined as $P^a/P_d - 1$, where P^a is the average price of all the executed trades in the order and P_d is the closing price for the stock on the day before the trade. Explicit trading costs are defined as (commission per stock/P_d). Costs are reported as percentages. Standard deviations are in parentheses. "vw avg" are value-weighted averages.

		Costs			n
		Total	Implicit	Explicit	
All trades	mean	0.12	0.09	0.03	3909
	stdev	(1.95)	(1.95)	(0.14)	
	vw avg	0.30	0.29	0.01	
Crosses only	mean	0.09	0.06	0.03	3252
	stdev	(2.01)	(2.01)	(0.15)	
	vw avg	0.27	0.27	0.01	
Market only	mean	0.30	0.25	0.05	657
	stdev	(1.60)	(1.60)	(0.04)	
	vw avg	0.46	0.43	0.03	

The total transactions cost for an order that was successfully crossed was on average 0.09. Conditional on a failure to cross, the average cost was 0.30; however, we should keep in mind that the sensitivity to market movements in our study may be problematic for the market trades. [14] Our results are in line with the finding in Conrad et al. (2003) that the costs for orders sent to alternative trading systems are lower than the costs for broker-filled orders. Our cost estimates also compare favorably with the results of Keim and Madhavan (1998), who found that the average cost for the smallest trade size quartile was 0.31 percent for exchange listed stocks, and that costs for higher quartiles were even higher. The median size of the trades in our sample is comparable to the Keim and Madhavan (1998) sample, but the Fund's trades are in stocks with larger market capitalization. This can explain part of the difference in estimated cost, since the costs in Keim and Madhavan (1998) were lowest in the stocks with highest market capitalization.

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[14] For the orders that were executed on the day following the initial attempt at internal crossing, the total cost could 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 the primary market. Table 6 in Næs and Skjeltorp (2003) reports implicit costs for the Fund which is decomposed into these two components.

Existing literature shows that measured trading costs are sensitive to various properties of the trade, such as order size, firm volatility and firm size. We control for these factors in our cost comparison by adopting the standard regression approach used in studies like those of Keim and Madhavan (1997) and Jones and Lipson (1999). From the determinants of trading costs in these studies we include as explanatory variables: a variable for order size, reflecting the fact that large orders are more expensive than small orders; a variable for liquidity, reflecting a negative relationship between execution costs and stock liquidity; a variable for total market activity, reflecting the potentially greater ease of trading when market activity is high; a variable for "adverse momentum," reflecting the greater difficulty of executing a buy order when prices are rising, and a variable for intraday volatility, reflecting the fact that it is more difficult to trade when markets are volatile. Order size is measured by the number of shares in the order. We use the market capitalization of the stock traded as our liquidity measure, and the number of shares in the stock traded on the NYSE on the day before the transaction as our measure of market activity. Adverse momentum is measured by total returns over the two days preceding the transaction, and our intraday volatility measure is the difference between the highest and lowest mid-quote on the day before the transaction.[15]

To measure the difference between market orders and crossed orders we add a dummy variable equal to one if the order is a market order. The sign and magnitude of this variable will measure the cost difference between a market trade and a cross. Since we want a pure measure of this cost difference, we control for cases in which orders were partially filled, again using a dummy variable. Finally, we include a dummy variable for the few cases of external crosses.[16]

The estimated regression model and the results are presented in Table 4. The dummy for market orders is 0.0036. Thus, controlling for trade difficulty and partial fills, a market order has a measured trading cost which is 36 basis points higher than an internally crossed order. By way of comparison, Conrad

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[15] Another variable which is often added to regressions of this type is a measure of the stock price. This is meant to correct for cases in which a low price and a fixed tick size make the costs disproportionally high. In the present case, the minimum price in the sample is about 9.50, which makes us believe this is not a major issue. Price is also problematic because it is highly negatively correlated with order size. This is due to a peculiarity of the present sample. The investor was an index tracker buying the whole index. When buying low-priced stocks, one has to buy more stocks. We therefore do not include this variable.

[16] By using dummy variables we assume a linear and additive relationship. This should be viewed as an approximation; we have no good model for arguing for any particular nonlinear functional form. This assumption is typically made in the literature, e.g., Keim and Madhavan (1997) and Conrad et al. (2003).

Table 4 Regression analysis of total trading costs for all orders

The table reports the results from estimation of the regression model

$$TC_i = \beta_0 + \beta_1 \ln(MCap_i) + \beta_2 \ln(Ord_i) + \beta_3 \ln(MktVlm_{i,t-1})$$

$$+\beta_4 R_{i,t-3,t-1} + \beta_5 HL_{i,t-1} + \beta_6 D_i^{EC} + \beta_7 D_i^M + \beta_8 D_i^P + \varepsilon_i$$

where, for trade i, $MCap_i$ is the market capitalization of the stock traded, Ord_i is the order size, measured as the number of shares in the order, $MktVlm_{i,t-1}$ is the number of shares in the stock traded on the NYSE on the day before the transaction, $R_{t-3,t-1}$ is total returns over the two days preceding the transaction, $HL_{i,t-1}$ is the difference between the highest and lowest mid-quote on the day before the transaction. D_i^{EC} is a dummy variable equal to one for stocks that were externally crossed, D_i^M is a dummy variable equal to one for stocks that were bought in the market and D_i^P is a dummy variable equal to one if the order is partially filled. ln() is the natural logarithm. The model is estimated using all orders in the data sample for which we can extract returns data and data on market capitalization from Datastream. In the table, the first column lists the variable, the second the coefficient estimate and the third the probability value of the coefficient being nonzero.

	coeff	(pvalue)
Constant	-0.0076	(0.04)
$\ln(MCap_i)$	-0.0008	(0.04)
$\ln(Ord_i)$	0.0014	(0.00)
$\ln(MktVlm_{i,t-1})$	0.0004	(0.20)
$R_{i,t-3,t-1}$	0.0001	(0.58)
$HL_{i,t-1}$	0.0001	(0.60)
D_i^{EC}	-0.0068	(0.00)
D_i^M	0.0036	(0.00)
D_i^P	-0.0099	(0.00)
n	3522	
$\bar{R}^2$	0.04	

et al. (2003) find that the costs of broker-filled orders were 31 and 28 basis points higher than, respectively, the costs of day crosses on POSIT and the after-hours crosses on Instinet. By contrast, the dummy variable for externally crossed orders in our sample has a significant negative coefficient, indicating lower costs for these orders after controlling for the trade difficulty variables. The cost estimates of externally crossed orders should be interpreted with some caution, however, as such observations have only been made on a few occasions.

The coefficient for market cap is negative, implying a lower cost for large firms. We also find a significantly positive coefficient for order size, implying that a larger order has a higher cost. Both of these results are typical findings in the literature. [17] For our sample, where most trades are internal crosses, the result

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[17] Keim and Madhavan (1997), Jones and Lipson (1999), Conrad et al. (2001) and

for the order size variable is a bit puzzling. The implication is that larger buy orders seem to be crossed on up-market days. We find a positive coefficient for $MktVlm$, the measure of trade activity. The implication is that the more "popular" stocks involve higher costs. This variable is, however, not significant. We also find that the measures of current return and current volatility have insignificant effects on trading costs.

Our results thus show that the measured ex post costs of trading in the main market are significantly higher than the costs of trading in the crossing network, even controlling for properties of the orders.

4 Adverse selection in crossing networks

In this section, we investigate whether there is evidence of informed trading in the crossing network. We first discuss how the presence of private information might affect trading in a crossing network. We then apply an event study to measure the extent of the private information. Finally, we use a probit analysis to model empirically the probability of crossing and its determinants, and show that our measures of private information affect the crossing probability in the predicted way.

4.1 Detecting private information in crossing networks

Investors with private information have an idea of which stocks are undervalued or overvalued and use this information in their trading decisions. Market microstructure theory shows how suspicions of private information will be reflected in implicit trading costs, and how prices gradually come to reflect private information as rational uninformed investors observe trading behavior in the market. Now, consider a crossing network. Orders in a crossing network cannot directly affect price, whether the investors are informed or not. Thus, by submitting their orders to a crossing network, informed investors can postpone disclosure of their information. Moreover, by removing trading volume from the primary market, price discovery will be delayed there. Thus, trader anonymity combined with lack of price discovery makes crossing networks particularly attractive to privately informed investors (provided that the information is not too short-lived).

However, crossing networks will not be completely unaffected by privately informed traders. Informed trading will affect the crossing probability, i.e.,

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Conrad et al. (2003) all find that these variables are significant and have the same signs.

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for a buyer it will be easier to cross a bad stock than a good stock. This fact suggests a way to gauge whether or not there are informed investors in a network: if there are informed investors, the performance of stocks which are easy to buy (sell) in the network should tend to be lower (higher) than the performance of stocks that are hard to buy (sell). Otherwise, if there are only liquidity traders, the probability of getting an order crossed should be a result of the random idiosyncratic preferences of these liquidity traders, and therefore completely unrelated to the subsequent performance of the desired stocks.

Because of the particular trading strategy followed by the Fund, we know the identity of stocks that were successfully crossed and stocks that were not. We also know that this is due to external market factors, not the choice of the order submitter. Our data are therefore well-suited to test for evidence of informed traders' participation in a crossing network, a task to which we now turn.

4.2 Event study

We investigate the presence of private information by performing an event study where we use the difference in cumulative abnormal return (CAR) for the two groups of stocks as a proxy for performance differences. Note that by looking at the *difference* in the CARs of the two groups, crossed and market orders, executed on the same date, we avoid any problem of sensitivity to market movements in cost measurement.

In order to perform the event study, for each stock i, we compare the daily actual return (R_{it}) with an estimate of its "expected return" $(\widehat{E[R_{it}]})$. The abnormal return is the difference:

$$\widehat{AR}_{it} = R_{it} - \widehat{E[R_{it}]}$$

We employ the market model as an estimate of expected return.[18] The CAR is found by aggregating these abnormal returns over time.

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[18] According to the discussion in chapter 4 of Campbell et al. (1997), the market model does not produce very different conclusions from alternative methods, and is much simpler to perform. We have also considered alternative expected return specifications, such as the CAPM, but find the results are not sensitive to this specification. The market model produces the estimate of expected return as $\widehat{E[R_{it}]} = \alpha_i + \beta_i R_{mt}$ where R_{mt} is the observed market return for date t. We use daily stock returns for two years preceding the "event" to estimate α_i and β_i for each stock i. The S&P 500 is used as the market index in the estimation.

This event study should be performed with some care. We want to consider cases in which the Fund first tried to cross and then immediately went to the market to buy the stocks not obtained in the crossing network. There are only three such cases of significant market orders by the Fund, and of these, the most relevant is the last occasion, when the Fund had to "fill" all the stocks in its desired portfolio. Therefore, we look at this case first. In Figure 1, we plot the evolution of the average CARs of the two sets of orders, crosses and market orders. [19]


Fig. 1 Event Study

The plot illustrates the results of the June event study. An event is an occasion on which the Fund tried to purchase a set of shares in the crossing network, and then went to the market to acquire the shares they were not able to buy in the crossing network. We calculate excess returns by using the market model to estimate the expected return: $\widehat{E[R_{it}]} = \alpha_i + \beta_i R_{mt}$, where R_{mt} is the observed market return for date t. Daily returns for the two years preceding the "event" are used to estimate α_i and β_i for each stock i. The S&P 500 is used as the market index in the estimation. Excess return is the difference between the actual return and this expected return, $AR_{it} = E[R_{it}] - R_{it}$. CAR is estimated by cumulating these excess returns. The figure compares the average cumulative abnormal returns for orders that were crossed and market orders for two subsequent dates in June (dates 15 and 16 in Table 1). The average is a value-weighted average using firm market value weights. We remove equities that were partially filled in both markets. The study uses 104 crosses and 160 market orders. Partial fills are 23% of the cases.

Panel A: CARs
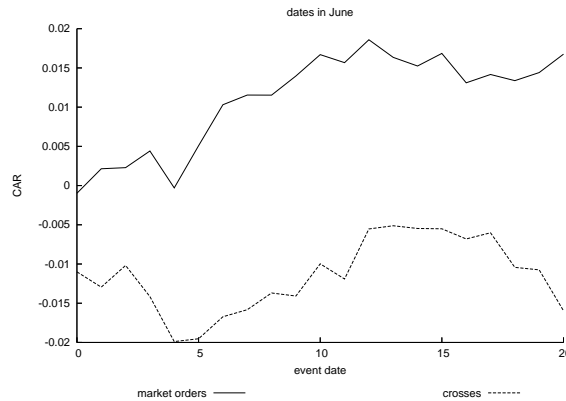
Panel B: Difference in CARs
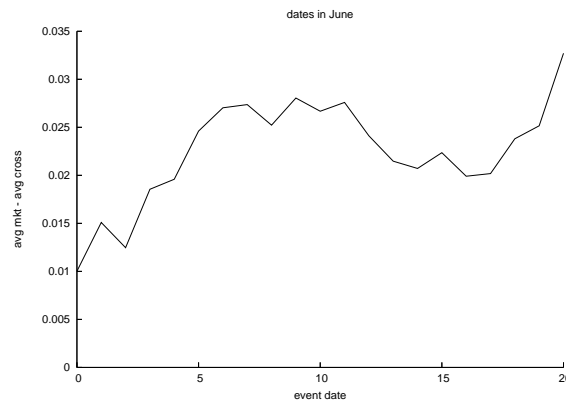
The difference between the two groups of stocks is striking. The market orders

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[19] Since the Fund matches a value-weighted index, we calculate the value-weighted average using firm value weights in this figure.

have a CAR increasing to almost 2%, which seems to indicate that the "good" stocks are difficult to obtain in the crossing network. The CAR for the crosses exhibits more pronounced immediate movement, with a one percent fall the day of the cross attempt. The stocks acquired in the crossing network were thus the ones that were not really wanted so early.

We posit that the difference in CARs is evidence of the presence of informed traders. We investigate the plausibility of alternative explanations below, but we have problems in seeing how any differences in liquidity and other measures of trade difficulty can induce such a return differential over a month. [20]

In a manner similar to our investigation of cost differentials, we want to test whether the difference in CARs for crossed orders and market orders is statistically significant when we control for other factors. To this end, we estimate a regression model explaining the cumulative abnormal return, starting on the trade date t and accumulating for 20 trading days, $CAR_{i,t,t+20}$.

The first explanatory variable we consider is the company's market value. This is included to control for the possibility that investors might demand a liquidity premium for holding smaller companies that is not fully reflected in our estimate of beta. If so, one would expect that the smaller the company, the higher the ex post CAR should be. However, as all the stocks in the sample are index constituents, there may be little difference in liquidity due to size, since they are all large firms. Because our conditional cost estimates indicate a size effect, we also control for order size in the regression. The recent return on the stock is included to control for short-term return reversals or continuations. [21] Two measures of stock variability and a measure of relative trading activity are included to proxy for the presence of private information. Variability may be related to informed trading in the sense that the value of being informed is higher for more volatile stocks. We use two measures of variability, high

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[20] It may at this point be helpful for intuition to consider how one could construct a trading strategy to exploit these results. What we find is that the fact that a stock is not available in a crossing network is a positive signal. To exploit this you could send a small buy order to a crossing network, and then buy in the market the stocks you did not acquire in the crossing network, possibly combined with short positions in the stocks you *were* able to cross. In fact, this is a real world strategy described to us at a conference where we presented our paper. Some investors "ping" a crossing network by sending a small order, and use the lack of success in the cross as a buy signal.

[21] The literature on the profitability of short-term momentum strategies is extensive, and there is little consensus about its existence and direction. A recent paper on the issue, Lewellen (2002) and particularly the discussion of this paper by Chen and Hong (2002), give some pointers to relevant papers. We choose to be agnostic about the type of strategy; the sign of the coefficient will determine whether it is reversal or momentum.

minus low and return volatility, because they may measure different properties. "High minus Low" is the difference between the high and low price observed the previous trading day, and may therefore be better at capturing short-term changes in variability. We measure volatility from return data for the previous 3 months (60 trading days), which may be better at capturing longer term differences in variability. The correlation between these two measures of variability is as low as 0.08, indicating that they may indeed be capturing different stock properties. We construct a variable for relative trading activity of the stock in the primary market by dividing the trading volume on a given date by the average daily trading volume for the same stock during the relevant month. To reduce the noise of the measure we calculate it for the two trading days prior to order submission by the Fund. This number gives an indication of whether the day had a higher- or lower-than-usual trading volume. A high value signifies a stock which is currently actively traded in the primary market. We believe that a high value for this variable is a proxy for informed trading in the primary market because informed traders add to the usual crowd of traders. To avoid problems due to the fact that this investigation is only performed on a few dates, we add dummy variables to control for fixed date effects.

We finally include a dummy variable for whether the order was crossed. If a cross outcome is merely a proxy for the other variables, the cross dummy should not be significant; the other variables should explain all the CAR differences.

Table 5 details the regression specification and the results. The variables that show a significant effect on the CAR are the constant, the market value of the company, the order size, one of the three proxies for private information and the cross dummy. The constant measures effects common to all securities, such as market movement. The market value of the company has a significantly positive effect on the CAR. This is not in accordance with a liquidity premium explanation. As mentioned, however, all the stocks in our sample are quite liquid. HL, the significant measure of volatility, has a positive coefficient. To the extent that volatility proxies for information, this result gives additional support to the information hypothesis, if we interpret this as CAR's being larger for more volatile stocks where information is more valuable.

Note that the cross dummy has a significant negative coefficient of -0.027. When we control for the other determinants, the return differential between crossed stocks and stocks that had to be bought in the market is thus 2.7 percent over the month after the cross. This is very similar to what we found in the June event study. Our results thus lend support to the prediction that informed investors will try to exploit their information in a crossing network

Table 5 Determinants of CAR

The table shows the results of a regression

$$CAR_{i,t,t+20} = \beta_0 + \beta_1 \ln(MCap_i) + \beta_2 \ln(Ord_i) + \beta_3 R_{i,t-6,t-1} + \beta_4 HL_{i,t-1} + \beta_5 \sigma(R_{i,t-60,t-1})$$

$$+ \beta_6 RelVlm_{i,t-2,t-1} + \beta_7 D_i^{Cross} + \sum_{j=2}^{4} \gamma_j D^j + \varepsilon_i$$

where $CAR_{i,t,t+20}$, the cumulative abnormal return over the 20 trading days following the attempt to cross, is the dependent variable. Explanatory variables are $MCap_i$, the company market value, Ord_i, the size of the order in number of shares, $R_{i,t-6,t-1}$, the return on stock i over the week before the attempt to cross, $HL_{i,t-1}$, high minus low, the difference between the highest and lowest price for stock i on the date before the attempt to cross, $\sigma(R_{i,t-60,t-1})$, stock return volatility for stock i in the two months before the attempt to cross and $RelVlm_{i,t-2,t-1}$, the average relative volume for the two days before the attempt to cross, where relative volume is defined as the trading volume in the primary market divided by the average daily volume in the primary market for the month. $\ln()$ is the natural logarithm. D_i^{Cross} is a dummy variable equal to one if the trade was executed in the crossing network. We finally add dummy variables D^j for dates to adjust for fixed date effects. The regression uses data for all the dates on which there are both crosses and market orders. In the table, the first column lists the variable, the second the coefficient estimate, the third the estimated standard deviation, and the last column the probability value of the coefficient being nonzero, using a normal distribution.

	coeff	(pvalue)
Constant	-0.081	(0.00)
$\ln(MCap_i)$	0.006	(0.06)
$\ln(Ord_i)$	0.007	(0.04)
$R_{i,t-6,t-1}$	-0.000	(0.67)
$HL_{i,t-1}$	0.013	(0.00)
$\sigma(R_{i,t-60,t-1})$	-0.182	(0.62)
$RelVlm_{i,t-2,t-1}$	-0.010	(0.10)
D_i^{Cross}	-0.027	(0.01)
Date 2	-0.032	(0.00)
Date 3	-0.031	(0.00)
Date 4	-0.050	(0.00)
n	1100	
$\bar{R}^2$	0.05	

first. [22]

4.3 A probit model of crossing success

We have argued that in the presence of private information, the probability of crossing will be a function of this private information. To look more closely at

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[22] This is a prediction of the Hendershott and Mendelson (2000) model.

this notion, we perform a probit type regression analysis in which the probability of success in the crossing network is treated as the endogenous variable. What we particularly want to establish is whether this probability is linked to the CAR difference between crossed and non-crossed orders, which is used as a proxy for the presence of private information.[23] Referring to equation (2), we are attempting to model p(cross) using a probit model. The probit type of analysis is similar to the one used in Conrad et al. (2003) and others to investigate the determinants of order routing decisions. In our case, the application is slightly different, because the cross or market decision is not endogenous to the *submitter* of an order. An attempt is made to cross all orders first. What we model with our probit model is the reaction of *other* participants in the crossing network.

In addition to the CAR we control for a number of other variables believed to be relevant for whether a stock is crossed. The literature on why traders may decide to trade outside exchanges tells us that a suitable model for the right-hand side of the equation should include variables for order size and stock liquidity. To measure whether crossing success is related to the activity in the underlying stock, we include the relative trading volume for the stock the day of the order. We also include the relative trading volume two days before the order is submitted, the short-term return on the stock to control for price reversals and continuations, and finally two measures of stock variability. These last variables are again related to information, and will, if significant, add to the argument that whether stocks are crossed or not is information-related.

Table 6 presents the estimation results. These estimates show the effects of changes in one of the explanatory variables on the probability that an order will be crossed. Let us first look at the coefficient on CAR. The coefficient is -1.372 with a p-value of 1 percent. Thus, it shows that the stocks with a higher CAR had a lower probability of being crossed. This is consistent with the information hypothesis.

The order size effect is negative and the market capitalization effect is positive. Hence, the data support the cream-skimming hypothesis of Easley et al. (1996). However, one should keep in mind that the stocks in our data set are all very liquid. Moreover, we would expect a negative effect due to order size simply because the participants in the network are competing for a fixed number of offered shares, i.e., the larger the order, the harder it will be to fill it in the network. Additionally, given that a crossing network exhibits positive

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[23] Note that the CAR is unobservable at the time of order submission. We are thus using ex post variables in this probit. This can be justified by assuming that informed traders have knowledge about the CAR which is used in their trading decisions.

Table 6 Probit model estimating determinants of probability of a cross

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

$$Prob(Y = Cross) = F\left(\beta'\mathbf{x}\right)$$

where $\mathbf{x}$ is the vector of explanatory variables, β the vector of coefficients, and $F(\cdot)$ a cumulative distribution function. Success in the probit is defined as a cross. Explanatory variables are $MCap_i$, the company market value, Ord_i, the size of the order in number of shares, $R_{i,t-6,t-1}$, the return on stock i over the week before the attempt to cross, $HL_{i,t-1}$, high minus low, the difference between the highest and lowest price for stock i on the date before the attempt to cross, $\sigma(R_{i,t-60,t-1})$, stock return volatility for stock i in the two months before the attempt to cross, $RelVlm_{i,t-2,t-1}$ and $RelVlm_{i,t}$, the relative volume for the two days before the attempt to cross and the date of the cross, respectively, and $CAR_{i,t,t+20}$ is the cumulative abnormal return over the 20 trading days following the attempt to cross. The relative volume is defined as the total trading volume in the primary market divided by the average daily volume in the primary market for the month. ln() is the natural logarithm. The model is estimated for the same set of trades as those used in the event studies. The total dataset contains 950 transactions, of which 372 were crosses. In the table, the first column lists the variable, the second the coefficient estimate and the third the estimated probability for the coefficient being nonzero, using a normal distribution.

Variable	coeff	(pvalue)
constant	-2.147	(0.00)
$CAR_{i,t,t+20}$	-1.372	(0.01)
$\ln(MCap_i)$	0.333	(0.00)
$\ln(Ord_i)$	-0.129	(0.01)
$R_{i,t-6,t-1}$	-0.047	(0.00)
$HL_{i,t-1}$	-0.004	(0.95)
$RelVlm_{i,t-2,t-1}$	0.216	(0.06)
$RelVlm_{i,t}$	-0.333	(0.00)
n	950	
Pseudo R^2	0.059	

network externalities (in the probability of a cross), it is possible that market cap is a measure of trading activity reflecting this. [24]

Interestingly, the coefficient of the last two days' return is significantly negative; equities which have had a large positive return the last couple of days are harder to find in the crossing network. The use of short-term continuation strategies by market participants may thus explain some of the CAR differential. [25]

Note that the last two variables, which are proxying for the trading activity being above or below the normal in the main market, are both significant, but have different signs. Stocks that were crossed had a lower-than-usual main

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[24] This point was suggested by an anonymous referee.

[25] This is consistent with the evidence on the prevalence of momentum trading by institutional investors in Griffin et al. (2003).

market volume the day of the cross, indicated by the negative coefficient of the $RelVol_{i,t}$ variable. A possible explanation is that we see signs of reduced activity in the main market in periods of higher crossing activity. Also, the crossed stocks showed higher trading activity the two days *before* the cross. This is consistent with anticipatory trading: participants in the crossing network who know that there is a large uninformed buy order coming may want to position themselves to exploit it, either by selling in the crossing network, or because the large buy is going to push up prices. However, this is not the only possible explanation. Trading activity may simply be related to information, which we have seen affects the crossing probability.

One observation to make here is that on average, we seem to see low primary market volume combined with price increases and high crossed volume.

5 Conclusion

We have shown that measured trading costs in crossing networks are significantly lower than measured trading costs on exchanges, and that information is important for whether an order is executed on an electronic crossing network. The last result is the most important contribution of the paper, demonstrating that informational asymmetries affect trading in crossing networks, even for the most liquid US stocks, the constituents of the S&P 500.

This result has implications for both strands of the market microstructure literature discussed earlier. Starting with the literature on intermarket competition, our result about information affecting market participation shows that although the new electronic marketplaces have a direct cost advantage relative to traditional exchanges, the information aggregation properties of alternative trading systems need to be investigated before we can draw any conclusion about the inevitability of the electronic market place.

With respect to the literature on costs of equity trading, we have shown that the question posed in the title of the paper, to cross or not to cross, is not as simple as proponents of crossing would have traders to believe. The low cost estimates we find for crossed stocks have to be weighed against the delay component of trading. Would the transactions costs of stocks that were not successfully crossed have been significantly lower if they had been submitted to the market immediately? And if so, could this effect be large enough to outweigh the cost advantages of the orders one did manage to cross? To answer these questions one would have had to estimate directly the cost of alternative trading strategies, such as submitting everything to the market.

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