Equity Trading by Institutional Investors. To Cross or Not to Cross?

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Abstract

The costs to institutional investors of trading equity are of obvious practical as well as academic interest. To date, the empirical academic literature on this topic has concentrated on data from equity trading at organized exchanges. This paper adds to the extant research by including evidence on using alternative mechanisms for facilitating equity trading, so called "crossing." We use the equity trades of one large institutional investor, the Norwegian Petroleum Fund, to investigate the costs of trading equity using such alternative trading venues. The results show that for trades that *were* crossed, the average implicit and explicit costs were lower than found in similar cases in the academic literature. We do, however, find that the orders that did *not* get crossed were special. By conducting an event study we discover the presence of "adverse selection:" The "best" stocks do *not* get crossed.

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The costs to institutional investors of trading equity are of obvious practical as well as academic interest. The academic literature on this issue, much of which is summarized in Keim and Madhavan [1998], shows there to be many unresolved issues, both regarding the components of the costs and the magnitude of the costs. Total trading costs include explicit components such as brokers fees and implicit components such as spread costs, price impact costs, and costs of non-trading. The implicit components are economically significant both compared with explicit costs and relative to realized portfolio returns. Trading costs are shown to vary systematically with trade difficulty, order placement strategy, market design, investment style, trading ability, and reputation. Accurate prediction of total costs is hard, and requires detailed data on the entire order submission process, including decision variables such as the trading horizon.

To date, most empirical academic literature has concentrated on data from equity trading at organized exchanges. We use equity trades of one large institutional investor, The Norwegian Petroleum fund (hereafter "the fund"), to provide evidence on the use of alternative mechanisms for facilitating equity trading.

The focus of the paper is on the strategy for implementing the actual equity transactions. There are different ways of transacting in equity markets. One can trade at established exchanges, or trade off market through so called "crossing networks". In a crossing network, participants typically submit desired quantities of a stock. Quantities are then matched, either automatically or manually. The agreed price is typically derived from a primary market, such as the closing price at NYSE.

There are several reasons to believe that a crossing network may provide reductions in the costs of trading equity for an investor such as the fund. First, crossing commissions are low compared to commissions charged by exchange brokers. Second, there is no bid-ask spread in a cross because liquidity is provided by the traders themselves and not by dealers. Finally, there is no direct price impact because prices in crossing networks are set independent 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. Also, we don't know what a crossed stock could have been bought or sold for in the open market, and thus it is hard to say how "good" the obtained price is. The anonymity provided by most crossing networks makes this trading method attractive to informed traders as well. Uninformed traders might therefore incur costs related to adverse selection. Since crossing networks do not guarantee execution, opportunity costs could also be significant (see Harris [1993] and Keim and Madhavan [1998]).

Our data on the fund's transactions in equities are special in that we know that the fund only traded in the market when particular stocks could not be crossed. Coupled with transaction data from the relevant exchange, our data set therefore enable us to look more closely at the costs related to adverse selection and missed trading opportunities for investors using a crossing network. We have chosen to use data for US equity markets. There are several reasons for this. We want to compare with extant research, most of which is done using US data. The practice of crossing is also most prevalent in the US market. Finally, it is easy to get relevant microstructure data for the NYSE.

While this paper uses data for only one trader, which may seem limited, the fund is quite representative for the group of institutional investors which is typically studied in the literature. To put some perspective on the applicability of the results of the paper, we show that the size of the fund's average transaction and number of transactions are of comparable magnitude to the data used in well known empirical papers dealing with this issue such as Keim and Madhavan [1997].

To get an idea of the fund's relative trade performance, we compare the fund's trading costs to relevant cost estimates reported in the literature. Because the different cost components of a trade are typically jointly determined, and because individual trades are often part of a larger package of trades, one cannot make inferences about the cost of a trade by adding up separate unconditional estimates of the component costs found in previous studies. To overcome these problems, we restrict the comparison to recent studies based on the implementation shortfall approach. The average cost of trades for the fund compares favorably to cost estimates reported in the literature for similar institutions. This may partly be due to the average costs of trading in equity markets having gone down in recent years. We therefore investigate whether the *causes* of costs are similar using a regression approach, and find that these are similar to other studies.

We do find that there are significant differences between crossed orders and market orders. We therefore look more closely at the costs of *not* getting an order crossed. First, we apply standard event study methods to compare the orders that were crossed with those that were not crossed in the same "round" of trades. The cumulative abnormal returns (CARs) on the stocks that were purchased in the market are found to be significantly higher in the period around the trade than the CARs for the stocks that were crossed. Thus, the stocks that could not be purchased through the fund's crossing network tended to be ones which did "better" than market expectations. To further investigate the data that underlies the event study, we perform a choice theoretic regression on the cross/market decision. The results from the binary choice regression confirms the impression that traders in crossing networks are faced with costs related to adverse selection. The "best" stocks do not get crossed.

The paper is structured as follows. Section 1 summarizes some of the relevant academic research on equity trading costs. We also have a short discussion of the theoretical impact of adding a trading venue, such as crossing. Section 2 gives a short overview of the petroleum fund and discusses the fund's strategy for submitting orders. We also describe the data sources used, and give some descriptive statistics on the data. In section 3, we compare the fund's trading costs to relevant cost estimates reported in the literature. In section 4, we look more closely at the costs of not getting an order crossed. Section 5 concludes.

1 Equity Trading Costs

1.1 Empirical evidence on trading costs

Much of the relevant research in this area is recently summarized in a paper by Keim and Madhavan [1998]. We will use their categorization of the costs of trading equity. These costs can be split into two main categories, explicit costs and implicit costs.

The explicit costs are the actual out of pocket costs of trading, such as brokers fees. These costs are easy to quantify. There has been a significant reduction in broker commissions in the US equity markets over the last decade. In another study by Keim and Madhavan [1997], the average commissions reported is 0.2% of trade value. Systematic variations in commission costs are documented, depending on what broker type and market mechanism investors use. There also seem to be a positive correlation between the explicit and implicit cost components of a trade, meaning that commissions tend to be higher the larger and more complex the trade is.

The implicit costs are much harder to quantify, and there are differences of opinion about their existence and relative significance. There are three main suggested components of the implicit costs: bid ask spread, price impact and opportunity costs.

The bid ask spread Consider the example of a specialist market structure like the NYSE. The specialist will at any time quote bid and ask prices valid for a given quantity, typically 1000 shares. The difference between the bid and ask price can be viewed as the price that the specialist demands for his services. Early work in market microstructure focused on the quoted spread, and used half of this spread as an estimate of the cost of a one way transaction. There are however problems using the quoted spread as a cost measure. Trades may occur inside the spread, if either the specialist or one of the "trading crowd" better the price. Quotes are only valid for the given quantity, not for larger quantities. Large blocks may be traded outside the exchange at negotiated prices.

These problems have lead several authors to propose measures of a "true" bid ask spread, often referred to as the "effective bid ask spread." These measures are ex post measures estimated from transaction prices, and try to find an "average" spread that a transaction was exposed to. Estimates of the effective spread tend to be considerably smaller than the quoted spread. Lee [1993], using an estimator based on quotation data, finds that the effective spread is only about half of the quoted spread. Madhavan et al. [1997], using a version of the serial covariance estimator first proposed by Roll [1984], find that the quoted spread was almost three times greater than the effective spread for a 1990 sample of 274 NYSE stocks.

Price impact costs The bid ask spread does not account for the fact that for large orders, prices may have to move in order to be able to execute the order. Or, in other words, traders may need to "walk the demand or supply curves." The resulting price impact may be decomposed into a temporary component reflecting the liquidity cost of the trade, and a permanent component reflecting possible new information. The information cost is related to the adverse selection problem studied in most of the theoretical market micro structure literature. There is always a risk that a given order is informed, and this risk is presumably larger for large orders.

In theory, the total price impact of a trade can be easily computed if one knows what the price of the stock would have been if the trade had not occurred. In practice, this so called "unperturbed" price is of course not observable. A common empirical measure of the price impact is the deviation between the transaction price and a proxy for the unperturbed price, where the proxy is some weighted average of pre- and/or post-trade prices for the stock.[1]

In studies of large-block trading it is common to focus on pre-trade benchmark prices. These studies document significant price impact for trades of 10000 shares and above. Keim and Madhavan [1996] show, however, that the choice of a benchmark price makes a large difference in the estimated price impact. Based on data on block-trades for one institutional investor, they find that the average price impact for a seller-initiated transaction vary from -4.3% to -10.2% when the unperturbed price is defined as respectively the previous day's close and the price three weeks before the trade. This result strongly suggests that the unperturbed price for block trades should be defined as the date on which the decision to trade was made.

Opportunity costs The final source of implicit costs of trading equity is the opportunity costs of not trading. These costs are due to the investor not being able to accurately implement the desired portfolio. Some orders may be delayed, during which time the market price may move in an undesirable direction. In other cases the investor may not be able to fill the order at all. For index trackers this cost may be important, because one may be exposed to "tracking errors" when the total portfolio deviates from the desired one.

Treynor [1981] has proposed a theoretical measure of the total cost of trading which incorporates all the mentioned cost components including the opportunity cost of not trading. This measure, which Perold [1988] called the "implementation shortfall", is defined as the difference in performance between the portfolio of actual trades and a matching "paper" portfolio where the stock returns are computed assuming that the trades were executed at the prices prevailing on the dates of the decision to trade. In addition to capturing all relevant cost components, the implementation shortfall overcomes the problem of measuring costs on an individual trade basis when the order consists of a package of sub-trades.

[1] This measure captures one-half of the bid-ask spread plus the price impact.

To correctly measure the opportunity cost of not trading, more detailed data are necessary than those readily available to most researchers. First, data on the date of the decision to trade are required. Second, researchers should have detailed information on the underlying motivations for the trade, such as investment objectives, target price, and trade horizon. Even this may be insufficient, however, because a strictly correct measurement sometimes will require unavailable information such as the data on trades that never took place.

Fortunately, relevant data on the order submission process of institutional investors have been made increasingly available. As a result, more recent empirical studies are in fact based on the implementation shortfall approach.

1.2 Alternative trading venues

In this paper we are concerned with "crossing" where the *price discovery* is elsewhere, there is some *primary market* from which prices are derived. While there is a large body of literature in the market microstructure literature comparing different exchanges,[2] this work is mainly concerned with settings with multiple opportunities for price discovery. There is little work in the literature concerned with alternative venues for trading such as discussed in our paper.

In an interesting theoretical piece, Hendershott and Mendelson [1999] looks at the coexistence of exchanges and crossing networks. They show that there are subtle interactions between the two markets, 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."

Fong et al. [1999] use detailed data from the Australian stock exchange (ASX) to study the competition between exchanges and alternative trading mechanisms such as upstairs markets, after-hours trading and electronic crossing markets. Two different explanations for why traders may decide to trade outside exchanges are summarized in the paper. Models emphasizing *asymmetric information*, such as Easley et al. [1996], explain off-market trading as driven by "cream skimming" of orders originated from uninformed traders. If so, trading outside exchanges will be directly competing with the primary market, and will be more likely for small orders in liquid securities. In contrast, *reputation models* (Seppi [1990]) explain trading outside exchanges by its ability to screen out informed investors and permit mutually advantageous trades off-market. If so, trading

[2] Theoretical examples include Madhavan [1992] and Glosten [1994]. Empirical examples include the many comparisons across NYSE and NASDAQ: Lee [1993], Huang and Stoll [1996], LaPlante and Muscarella [1997], Keim and Madhavan [1996], Keim and Madhavan [1997] and Chan and Lakonishok [1997], among others.

outside exchanges will be largely complementary to exchange trading, and will be more likely for large orders, especially in less liquid stocks. Fong et al. [1999] find support for an asymmetric information explanation.

We are not aware of any empirical work using the kind of data we have access to in this paper.

2 Institutions and Data

In this section we first give some institutional background on the investor before summarizing the data sources and describing the data.

2.1 The Norwegian Government Petroleum Fund.

Let us first give some remarks on the source of transactions. The Norwegian Government Petroleum Fund was established in 1990 by the Norwegian Government. The fund is a vehicle for investing the Government's income from petroleum related activities in international capital markets. The Ministry of Finance delegates the operational portfolio management of the fund to Norges Bank (the Central Bank). Norges Bank has a mandate to optimize the returns on the investments subject to investment criteria set by the Ministry of Finance. The investment criteria is currently based on performance relative to a benchmark portfolio.

Funds were allocated for the first time in 1996 and invested according to the guidelines used for the foreign exchange reserves. By the end of 1997 the fund value was about USD 15.4 billion, invested mainly in foreign government securities. In October 1997 the Ministry of Finance gave new criteria for the composition of the fund, to apply from 1 January 1998. The new guidelines stated that between 30% and 50% of the fund were to be invested in equity securities. The composition of the fund portfolio was changed into partly equity during the first half of 1998, by buying equity in (mainly developed) foreign markets. Our data is from this "buildup" period by the fund, in which the fund was a large buyer of equity. By the end of June 1998, the market value of the total Petroleum Fund portfolio was USD 17.7 billion, and the market value of the stock portfolio was USD 7.2 billion. US stocks represent 28.5% of the benchmark portfolio for the equity securities.

The fund employed four index managers to establish the equity portfolio. One of the index managers was chosen as "transition manager". The transition manager was given a set of desired securities, and was told to cross as many stocks as possible. The stocks that could not be purchased from the transition manager's own customers (internal cross), were tried purchased from the customers of the other three index managers or through an electronic crossing network such as Instinet (external cross). The stocks that could not be crossed at all were purchased in the market.

The "crosses" were ex ante set to be twice a month, but the transition manager could and did offer the fund "packets" at other dates. In practice, the transition manager offered the fund a "package" which the fund would accept or refuse. The exact composition of the package was not given, only indication of approximate content. Once acceptance was given, it took two days before the fund received the physical stocks. Most of the fund's trades ended up being crossed. For the first two months, crossing prices were set as the primary market (NYSE/NASDAQ) close that day. For the remainder of the period, prices were set as the value weighted average price (vwap) of trades in the primary market during the day.

Table 1 summarizes the implementation of the US part of the fund's equity portfolio. The portfolio was established in the period from January 1998 to June 1998. The total portfolio investment was \$1751 mill. Of this amount \$1501 mill or nearly 86 percent was crossed.[3] Market trades to complete the desired portfolio were concentrated at three out of sixteen trading dates. The highest trading volume on one date amounted to \$300 mill, or 17.1 percent of the total portfolio investment. Note that for the period we consider the fund was only buying, not selling securities.

2.2 Data sources

In addition to the actual trades by the fund, we also use market data. As a source for actual market data from the NYSE, such as volume and closing prices, we use the NYSE Trades and Quotes (TAQ) database for the period from January 1998 through June 1998.[4] For each of the stocks traded by the fund we search for data on this stock on the TAQ tape. In some cases we are not able to match the trade with TAQ data.[5] We also remove stocks that split around the fund's trades. In addition to the TAQ data Datastream is the source of data on (longer term) stock returns and market capitalization.

[3] For the entire stock portfolio, the corresponding percentage is 83.

[4] The TAQ data base includes historical trade prices and quantities, with their associated market conditions, transaction by transaction. The data are time-stamped to the nearest second. TAQ contains all equity transactions reported on the so called *Consolidated Tape*, which includes all transactions on NYSE, AMEX, NASDAQ and the regional exchanges.

[5] Some stocks in the fund's portfolio is not traded at NYSE, e.g. Microsoft. Except for one date, the matching percentage is in the 82 to 94 percentage range.

Table 1 Establishing the US stock portfolio.

Transaction volume in million $, for each date on which the fund traded. January to June 1998. For anonymity reasons we do not show the actual dates, but the table is in chronological order.

date	Crosses		Market	All
	Internal	External		
1	174			174
2	184			184
3		115		115
4	58		3	61
5	19			19
6		30		30
7	163		73	236
8	300			300
9	14			14
10	14			14
11	231			231
12	70			70
13	8			8
14	23			23
15	97			97
16			174	174
	1356	145	250	1751
Percent	77	8	14	

2.3 Descriptive statistics

Order size Market microstructure theory and empirics tell us that an important determinant of the cost of trading is an order's size. Unless it is known that a trader is uninformed, larger orders will, all else equal, have a bigger price impact. We therefore show some statistics on the size of the fund's orders. We consider two measures of order size, one absolute and one relative.

A common definition of a *large* order is an order of ten thousand shares or more. Table 2 give some summary statistics for the fund's trades, both in number of shares and in dollar values. As the table shows, most the fund's trades can not be classified as block trades, but an average order of $688 thousand for a sample of 4200 orders is not peanuts. The table is also split into data for crosses and market orders, to check for obvious differences between them. There seems to be little differences in sizes here. One thing to note that does not show up in the table is that some of the largest orders were done in the market. This may be a sign that it is problematic to "cross" very large volumes for one stock.

To put some further perspective on the size of the fund's trades we compare the order size to the

Table 2 Descriptive statistics for the size of transactions.

Averages of number of shares traded per transaction.

No Shares	mean	std	min	q1	median	q3	max	n
All orders	6898	9654	11	2000	3800	7700	115200	4200
Crosses only	7013	9661	19	2000	3800	8000	109400	3494
Market only	6329	9598	11	2000	3550	6900	115200	706

Averages of dollar values per transaction. Values in thousands of USD.

Trade value (in 1000$)	mean	std	min	q1	median	q3	max	n
All orders	386	688	0	87	174	373	9050	4200
Crosses only	396	683	0	89	177	389	8962	3494
Market only	339	710	12	83	157	300	9050	706

daily trading in the market for the same stock. We calculate what fraction the fund's trades were of the total quantities traded on the NYSE during a day. We look at both NYSE volumes on the day of the actual trade, and average daily NYSE volumes over the month of trade. Table 3 summarizes the relative trading volume against NYSE. The median relative volume is 0.8% of the total trading

Table 3 Relative trading volume for the fund's transactions.

Relative trading volume is defined as the percentage fraction of the fund's daily trade relative to the daily total volume at the NYSE. We use two measures for daily NYSE volume: The total volume traded at the NYSE that day for that particular stock, and the average daily NYSE trading volume during that month for that stock. Numbers in percent. *Mean* is an equally weighted average and *std* it's standard deviation. *Vw* is a value weighted average, using the value of the fund's trades as weights. *n* is the number of observations.

	Relative to	mean	std	vw	min	median	max	n
All orders	That day	1.4	2.67	1.7	0.00	0.9	100	3971
	That month	1.2	2.14	1.8	0.0	0.8	73.6	3972
Crosses	That day	1.3	2.56	1.6	0.00	0.9	100	3308
	That month	1.1	1.29	1.4	0.0	0.8	25.2	3308
Market	That day	1.8	3.11	2.0	0.01	1.0	36	663
	That month	1.8	4.31	4.0	0.0	0.9	73.6	664

during the day. This is probably a better measure than the mean, because the distribution is skewed to the right. This indicates that the fund's average trade was relatively modest compared to the daily NYSE trading.[6] The average trade is higher compared to trade "that day" than compared to average trading during "that month", suggesting that the fund did not in general trade on dates

[6]We also calculated the equally and value weighted averages for each trading date. Varying from one to two percent of daily transaction volume, these confirm the impression that the magnitude of the fund's transactions have been modest.

when trading activity in the market was peaking. As one can observe from the max column, there is at least one stock in which the fund was the whole market. This is truly a special case, it was an order of 700 shares in a thinly traded equity. The second highest relative volume was 40% of the day's trades. There is in fact only 10 cases where the fund's trades represented more than 20% of the market trading that day.

Clearly, by both metrics used above, the fund is not a dominant player in the US equity markets. But the fund is neither an unimportant player. In Keim and Madhavan [1997]'s study of large institutional investors, the median buy order size is reported to be $138 thousand. Measured in dollar values, the size of the fund's average order and median order were $386 thousand and $174 thousand respectively.[7]

Stock liquidity Liquidity is another important determinant of transaction costs. The better the stock liquidity, the less prices may have to move in order to be able to execute an order. Since the benchmark portfolio of this sample was the US stocks included in FT/S&P's Actuaries World Index, and the fund is tracking the index, the stocks in the sample will obviously be the more liquid stocks on the exchange. To confirm this table 4 gives some summary statistics of factors which are thought to be relevant for a stock's liquidity: The price of a stock, the market value of the company, and market activity for the stock. The average and median market capitalization of the stocks in the sample are $16.957 billion and $7.56 billion respectively. For comparison, Keim and Madhavan [1997] report a median market capitalization of the stocks in their sample of buy orders of $1.06 billion. "NYSE volume" is the number of shares traded in the stocks at the day preceding the fund's trade, and "NYSE trade" is the total number of orders in the stocks at the transaction day. The numbers for market capitalization and market activity are all highest for the crossed stocks. Hence, the stocks that were crossed seem to be a bit more liquid than the stocks that were purchased in the market.

3 Size and determinants of trading costs.

In this section we first look at the size of estimated transaction costs, and compare it to relevant cases in the literature. We then look at the determinants of our estimated transaction costs using a regression approach.

[7]Keim and Madhavan [1997]'s sample is compiled by the Plexus Group and contains all equity transactions of 21 institutional investors during 1991 to 1993.

Table 4 Summary statistics on stock liquidity.

"Price" is the stock price paid by the fund. "Market cap" is the market value of the company(in billions). "NYSE volume" is the number of shares (in millions) traded in the stock during the day preceding the fund's trade. "NYSE trades" is the total number of orders in the stock at the transaction day. Mean and median.

	Price		Market cap		NYSE volume		NYSE trades	
	mean	median	mean	median	mean	median	mean	median
All trades	52.9	48.2	16.9	7.5	1.1	0.5	644	245
Crosses	53.4	48.9	17.6	7.8	1.2	0.5	653	249
Market orders	50.7	44.9	13.6	6.1	0.8	0.3	599	231

3.1 Comparison with relevant cost estimates

As measures of trading cost, Keim and Madhavan [1998] use

$$\text{implicit cost} = \frac{P^a}{P_d} - 1$$

$$\text{explicit cost} = \frac{\text{Commission per share}}{P_d}.$$

where P^a is the average price of all the executed trades in the order and P_d is a benchmark price. In their analysis they use the closing price for the stock on the day before the decision to trade. Total trading costs is defined as the sum of these two. Table 5 is taken from their paper and gives results for applying these measures to a large sample of institutional orders.

We calculate the same measures of implicit and explicit trading costs for the fund's trades. The results are summarized in table 6. As the table shows, average costs of transactions for the Petroleum fund of 0.12% compares favorably to the sample of trades used by Keim and Madhavan [1998], where the average cost for the largest trade size quartile was 0.31%, and the cost for smaller quartiles even higher. It should be mentioned here that the time periods are not the same. Keim and Madhavan [1998]'s sample is for the period January 1991 to March 1993, and average costs of trading have probably declined since then.

To make further comparisons with Keim and Madhavan [1998], table 7 splits the trades into quartiles based on trade size. The table shows similar patterns. The costs are smallest for the largest orders, and increase with declining order size.[8]

[8] While we do not report it here, we have also calculated similar costs for portfolios sorted on market capitalization, and a similar pattern emerges. The stocks of the largest companies have the lowest costs.

Table 5 Measured trading costs for a sample of institutions, taken from table 4 of Keim and Madhavan [1998].

Average trading cost by trade size quartile for common stock trades for 21 institutions for the period January 1991 to March 1993.
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 decision to trade the stock. Explicit trading costs are defined as (Commision per share/P_d). The sample is partitioned by trade size quartile defined as number of shares traded divided by total outstanding shares, with quartile cutoffs determined separately for buy and sell transactions. Costs are reported in percent. Standard errors are in parenthesis.

	Exchange Listed Stocks				Nasdaq stocks	
Trade Size Quartile	Total	Implicit	Explicit	n	Total	n
Buyer-Initiated Trades						
Smallest	0.31	0.18	0.13	7,392	0.76	1,755
	(0.02)	(0.02)	(0.00)		(0.06)	
2	0.36	0.19	0.17	6,577	1.01	2,571
	(0.03)	(0.03)	(0.00)		(0.07)	
3	0.53	0.32	0.21	6,503	1.08	2,645
	(0.04)	(0.04)	(0.00)		(0.09)	
Largest	0.90	0.65	0.25	5,570	1.80	3,577
	(0.05)	(0.05)	(0.00)		(0.10)	
Seller-Initiated trades						
Smallest	0.33	0.15	0.18	5,736	0.29	696
2	0.31	0.11	0.20	5,291	0.50	1,142
3	0.38	0.17	0.21	4,766	0.71	1,666
Largest	1.42	1.13	0.29	3,830	2.63	2,602

Table 6 Average trading costs for the fund's transactions.

Average trading costs for the Norwegian Petroleum fund's transactions, January to June 1998. Costs are measured following 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 share/P_d). Costs are reported in percent. Standard errors 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	

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Table 7 Average trading costs for the fund's transactions, sorted by trade size

Average Trading Costs for the Norwegian Petroleum fund's transactions, January to June 1998. Costs are measured following 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 share/P_d). Trade Size sorted quartiles.

Trade Size quartile			Costs Total	Implicit	Explicit	n
Smallest	All trades	mean	-0.06	-0.14	0.08	978
		stdev	(2.06)	(2.08)	(0.27)	
	Crosses only	mean	-0.16	-0.25	0.09	796
		stdev	(2.13)	(2.14)	(0.30)	
	Market only	mean	0.38	0.32	0.06	182
		stdev	(1.67)	(1.67)	(0.05)	
3	All trades	mean	0.05	0.03	0.03	978
		stdev	(1.85)	(1.85)	(0.02)	
	Crosses only	mean	0.00	-0.02	0.02	800
		stdev	(1.91)	(1.91)	(0.00)	
	Market only	mean	0.30	0.25	0.05	178
		stdev	(1.57)	(1.57)	(0.03)	
2	All trades	mean	0.27	0.25	0.02	978
		stdev	(1.88)	(1.88)	(0.01)	
	Crosses only	mean	0.27	0.26	0.01	801
		stdev	(1.96)	(1.96)	(0.00)	
	Market only	mean	0.24	0.20	0.04	177
		stdev	(1.49)	(1.49)	(0.02)	
Largest	All trades	mean	0.23	0.23	0.01	978
		stdev	(1.96)	(1.96)	(0.01)	
	Crosses only	mean	0.23	0.22	0.00	858
		stdev	(2.00)	(2.00)	(0.00)	
	Market only	mean	0.28	0.25	0.03	120
		stdev	(1.68)	(1.68)	(0.02)	

In both table 6 and table 7 we also show cost estimates split on crossed orders and market orders. For example, the average cross has an average cost of 0.09 while a market order has an average cost of 0.30. The market orders are clearly "more expensive" using these metrics. But this may be an artifact of the order placement strategy, and we will spend some time investigating these differences in the remainder of the paper.

Because market orders are the "left over" orders that could not be crossed, they are typically purchased in the period just after they were first tried crossed. Hence, the relevant benchmark may not the closing price the day before the trade, but the closing price 2 or 3 days before. To do the comparison of the costs of market orders and crosses more correct, we calculate the costs using three different benchmarks $P_d = P_{t-1}$, $P_d = P_{t-2}$ and $P_d = P_{t-3}$, where P_{t-1}, P_{t-2} and P_{t-3} are the closing price respectively 1, 2 and 3 days before the trade date. Table 8 shows the results. The interesting observation from this table is the sudden sign reversal of the implicit cost of market orders if we use the closing price 2 days before as the benchmark.

Table 8 Average trading costs for the fund's transactions, using alternative benchmarks.

Average trading costs for the Norwegian Petroleum fund's transactions, January to June 1998. Costs are measured following 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 benchmark for comparison. We use three different benchmarks P_{t-1}, P_{t-2} and P_{t-3}, the closing prices respectively 1, 2 and 3 days before the trade date. Explicit trading costs are defined as (Commission per share/P_d).

			Benchmark						
			P_{t-1}		P_{t-2}		P_{t-3}		
		Explicit	Implicit	Total	Implicit	Total	Implicit	Total	n
All trades	mean	0.03	0.09	0.12	0.20	0.24	0.29	0.32	3909
	stdev		(1.95)		(2.86)		(3.57)		
Crosses only	mean	0.03	0.06	0.09	0.33	0.36	0.44	0.48	3252
	stdev		(2.01)		(2.93)		(3.66)		
Market only	mean	0.05	0.25	0.30	-0.40	-0.36	-0.49	-0.44	657
	stdev		(1.60)		(2.41)		(2.92)		

3.2 Determinants of trading costs

As the previous subsection shows, the magnitude of transaction costs have declined relative to the investigations referred to there. The obvious next question is whether the *determinants* of transaction costs have changed. To answer that question we estimate a regression model on total trading cost similar to the regression approaches in Keim and Madhavan [1997] and Jones and Lipson [1999]

Based on the determinants of trading costs in these studies, we include as explanatory variables: A variable for order size, reflecting 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 that trades are easier to accomplish when market activity is high, a variable for "adverse momentum," reflecting that it is more difficult to execute a buy order when prices are rising, a variable for intraday volatility, reflecting that it is more difficult to trade when markets are volatile, and the inverse of the stock price, reflecting effects on proportional costs of general price movements (fixed proportional costs are higher the lower the stock price).[9] Our regression model can be written,

$$\begin{aligned} TotCost_i &= \beta_0 + \beta_1 D_i^{CROSS} + \beta_2 InvPrice_i + \beta_3 LogMark_i + \beta_4 LogOrder_i \\ &\quad + \beta_5 MarkVol_i + \beta_6 Return_i^{MOM} + \beta_7 HighLow_i + \epsilon_i \end{aligned}$$

where, for order i, $TotCost$ is total trading costs in percent of the NYSE closing price on the day before the transaction, D^{CROSS} is a dummy variable for stocks that were crossed, $InvPrice$ is the inverse of the price per share of the stock traded, $LogMark$ is the logarithm of the market capitalization of the stock traded, $LogOrder$ is the logarithm of the order size measured in number of shares, $MarkVol$ is the number of shares traded at NYSE on the day before the transaction, $Return^{MOM}$ is total returns over the two days preceding the transaction, and $HighLow$ is the difference between the highest and lowest mid quote on the day before the transaction.

Table 9 presents the estimated coefficients of the regression model. We run separate regressions on the stocks that were crossed and the stocks that were purchased in the market. The total number of transactions is 3522, of which 2924 are crosses. The cross dummy captures any "order form" effects on trading costs that are unrelated to the other independent variables. As we would expect, this variable has a significant negative coefficient suggesting that crossing was less expensive than trading at NYSE. The coefficients of stock liquidity and order size are significant and have expected signs, however, they only explain a small part of the total variation in trading costs. These results are similar to those reported by Keim and Madhavan [1997], and Jones and Lipson [1999]. The coefficient of the price inverse is significant and negative. Keim and Madhavan [1997] report a significant and positive coefficient for this variable for buy orders as well as for sell orders.

[9] Keim and Madhavan [1997] examine the magnitude and determinants of transaction costs for a sample of institutional traders with different investment styles. Jones and Lipson [1999] compare transaction costs across NYSE, NASDAQ and AMEX using a sample of institutional equity orders in firms that switch exchanges.

Table 9 Regression analysis of total trading costs

We estimate the regression model $TotCost_i = \beta_0 + \beta_1 D_i^{CROSS} + \beta_2 InvPrice_i + \beta_3 LogMark_i + \beta_4 LogOrder_i + \beta_5 MarkVol_i + \beta_6 Return_i^{MOM} + \beta_7 HighLow_i + \epsilon_i$, where D^{CROSS} is a dummy variable for stocks that were crossed, $InvPrice$ is the inverse of the price per share of the stock traded, $LogMark$ is the logarithm of the market capitalization of the stock traded, $LogOrder$ is the logarithm of the order size measured in number of shares, $MarkVol$ is the number of shares traded at NYSE on the day before the transaction, $Return^{MOM}$ is total returns over the two days preceding the transaction, and $HighLow$ is the difference between the highest and lowest mid quote on the day before the transaction. The model is estimated on the whole data set and separately for the crossed orders and the market orders. The t-values (reported in parentheses) are based on heteroskedasticity consistent standard errors.

Variable	All trades		Crosses		Market orders	
$Constant$	0.266	(0.709)	0.098	(0.227)	0.659	(1.028)
$InvPrice$	-11.707	(-3.630)	-14.743	(-4.056)	6.975	(1.436)
$LogMark$	-0.164	(-3.482)	-0.188	(-3.360)	-0.037	(-0.525)
$LogOrder$	0.212	(4.703)	0.243	(4.585)	-0.061	(-0.882)
$MarkVol$	0.032	(1.148)	0.023	(0.780)	0.129	(1.475)
$Return^{MOM}$	0.017	(1.151)	0.037	(2.121)	-0.089	(-2.897)
$HighLow$	-0.003	(-0.289)	-0.005	(-0.388)	0.086	(1.028)
D^{CROSS}	-0.206	(-2.673)				
R^2	0.015		0.020		0.062	

In Jones and Lipson [1999], the price inverse coefficient is positive for orders in stocks that change listing from NASDAQ to NYSE, and negative for orders in stocks that change listing from AMEX to NYSE. A negative price inverse coefficient is not consistent with higher percentage spreads in low-priced stocks.

When splitting our sample, we see that the regression model does not work very well for the stocks that were purchased in the market. The only significant variable is the returns over the two days preceding the transaction. Note, however, that this variable has opposite effects on costs for market trades and crossed trades. If prices are generally rising, it seems to be *less* difficult (i.e. less expensive) to execute a buy order in the market, and more difficult to execute a buy order in the crossing network. This result confirm the impression that the stocks purchased in the market were special.

4 Adverse Selection in Crossing Networks

In this section we try to measure the adverse selection part of crossing, which is the cost of *not trading*. We first use an event study to show the presence of such costs, and then try to determine what are the prime causes of the "no cross" event.

4.1 Event Study

The comparison of costs in section 3 indicates that there are significant differences between orders that were "crossed" and orders that were not. To understand further these differences we perform an event study. The idea is that we want to understand what happens to the underlying stock around the time of the trade by comparing the "cumulative abnormal return" around the event (i.e. trade by the fund), and see if there are any differences across the two types of orders. Any such differences may indicate that there are special properties of the stocks that are not crossed, or, there may be *adverse selection*, the stocks that are *not* crossed may be the ones we "want."

For purposes of doing an event study, for each stock i we need to compare its daily actual return (R_{it}) with an estimate of "expected return" ($\widehat{E[R_{it}]}$). Abnormal return is the difference:

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

Following now standard practice,[10] as an estimate of expected return we apply the market model. The estimate of expected return is then

$$\widehat{E[R_t]} = \alpha_i + \beta_i R_{mt}$$

where R_{mt} is the observed market return for date t. Daily stock returns for the two years preceding the "event" are used to estimate α_i and β_i for each stock i.

To calculate the accumulated return over time, we aggregate into the "cumulative abnormal return." We choose to start measurement 20 trading days before the event and calculate

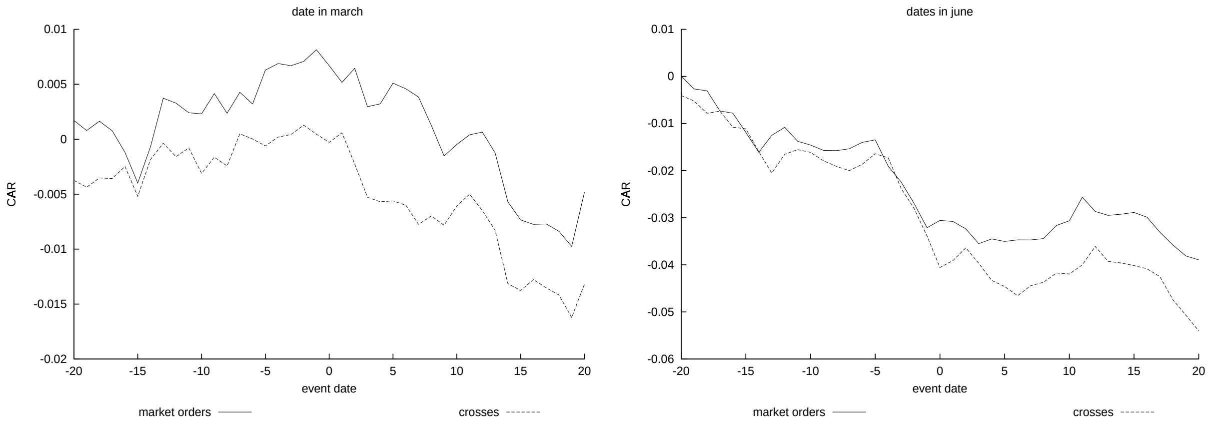
$$\widehat{CAR}_{iT} = \sum_{k=t-20}^{T} \widehat{AR}_{ik},$$

where t is the date of trade (event date). Some care has to be applied in the implementation of the event study. Since there were only two dates with significant market orders, we can not aggregate over all dates, essentially we have a small sample problem. The relevant comparison is between those orders that were crossed and those that were not crossed in the same "round" of trades. By round we mean that the cross and the market order were within 3 days of each other. With that criterion we are left with 2 sets of relevant dates, one in the middle of the period and one near the end, in which we have a comparable number of crosses and market orders within 2 days. Figure 1 shows the results for running event studies for the 2 dates. There is obviously something special

[10] See Campbell et al. [1997].

Figure 1 Event Study

Comparison of Cumulative Abnormal Returns for orders that were crossed and market orders, two dates with comparable trades. On the left date in March, on the right date in June. Study in March have 388 observations, study in June have 610 observations.



about the market trades, they have a higher CAR than the crosses that were done at the same date. This is confirmed using a test for the difference of mean CAR's. At both dates the difference is significant at the 1% level.[11]

4.2 Determinants of the "cross/no cross" event

To further investigate the data that underlies the event study, we want to analyze what factors determine whether a stock is crossed, or have to be bought in the market. To implement this we perform a choice theoretic regression on the cross/market decision. The probability of observing a cross is assumed to be given by the model

$$Prob[Y = Cross] = F[\beta'\mathbf{x}]$$

where $\mathbf{x}$ is the vector of explanatory variables, β is the vector of coefficients, and $F[.]$ is a cumulative distribution function.

The literature on why traders may decide to trade outside exchanges tells us that a suitable model for the right hand side of the regression equation should include variables for order size and stock liquidity.[12] To investigate the sign of adverse selection from our event study, we include

[11] These tests are adjusted for the event study nature of the data, as discussed in [Campbell et al., 1997, Ch 4.4]. Further details is available from the authors.

[12] See Easley et al. [1996] and Seppi [1990].

cumulative abnormal returns on the stocks up to the transaction date. Equation (1) summarizes the regression model we estimate

$$Prob[Y = Cross] = F[\beta_0 + \beta_1 LogMark_i + \beta_2 LogOrder_i + \beta_3 CAR_i^{t-20,t} + \epsilon_i] \quad (1)$$

where, for order i, $CAR^{t-20,t}$ is the abnormal cumulative returns on the stock from 20 days preceding the transaction to the transaction date. The total dataset contains 948 transactions of which 372 were crosses. We estimate equation (1) for the whole dataset, and separately for the two "rounds" of trades. The data set underlying "Date in March" contain 388 observations, of which only 94 are crosses. The data set underlying "Dates in June" contain 610 transactions of which 278 are crosses.

Table 10 presents the estimation results using a probit model.[13] In interpreting the model, we calculate 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 the group of crossed trades.[14]

For "all trades" and "dates in June", the estimation results are qualitatively the same. The order size effect is negative and the market capitalization effect is positive. Hence, the data supports an asymmetric information model.[15] The CAR variable has a significant negative effect on the probability of seeing a stock being crossed. Thus, the stocks that could not be purchased through the fund's crossing network tended to be the ones which did best over the last couple of weeks compared to market expectations. This evidence confirm the picture emerged from the event study: traders in crossing networks are faced with costs related to adverse selection. This result suggests that the feared negative effects from "off market" trading on the primary market ("cream-skimming" and use as "dealer of last resort") might be mitigated by the fact that "off market" traders face higher implicit costs in the form of adverse selection.

The estimated regression model does not seem to fit well for the "date in March" sample. The only significant variables are the constant term (negative) and the order size (positive).

[13]The probit model uses the normal distribution as $F(\cdot)$. To check our analysis we have also performed similar regressions using the linear probability model and the logit model. The three models produce quite similar results, and we only report estimation results from the probit model,

[14]In the case of a linear probability model, these derivatives are constant and equal to the coefficients. For non-linear probability models such as the probit and the logit model, we have that $\frac{\partial E[y|x]}{\partial x} = f(\beta' x)\beta$ where $f(.)$ is the density function corresponding to the cumulative distribution function $F(.)$. Hence, for these models the effects of changes in one of the explanatory variables will vary with the values of $\mathbf{x}$.

[15]However, one should keep in mind that the stocks in our data set are all very liquid, and that overall the fund's orders were quite small.

Table 10 Estimated probit model on the data underlying the event study.

We estimate the probit model, $Prob[Y = Cross] = F[\beta_0 + \beta_1 LogMark_i + \beta_2 LogOrder_i + \beta_3 CAR_i^{t-20,t} + \epsilon_i]$ where $F(\cdot)$ is the normal distribution, $LogMark$ is the logarithm of the market value of the company, $LogOrder$ is the logarithm of the order size measured in number of shares, and $CAR^{t-20,t}$ is the abnormal cumulative returns on the stock from 20 days preceding the trade to the transaction date. The model is estimated on the whole data set and separately for the two "rounds" of trade. Slope estimates (marginal effects) are calculated at the means of the regressors. The t-values (in parentheses) are based on robust standard errors.

	All trades		Date in March		Dates in June	
Variable	Coefficient	Slope	Coefficient	Slope	Coefficient	Slope
$Constant$	-2.095		-10.231		1.346	
	(-5.393)		(-8.850)		(2.534)	
$LogMark$	0.336	0.128	0.185	0.046	0.286	0.113
	(6.765)		(1.334)		(4.650)	
$LogOrder$	-0.150	-0,057	0.904	0.225	-0.491	-0.195
	(-3.222)		(5.937)		(-7.626)	
$CAR^{t-20,t}$	-2.122	-0,811	0.271	0.067	-1.285	-0.509
	(-3.919)		(0.180)		(1.952)	
$pseudo\ R^2$	0.049		0.425		0.098	

5 Conclusion

This paper has used data for the Norwegian Petroleum fund's transactions in the US equity market as a vehicle for measuring trading costs using alternative trading venues (crossing). While the petroleum fund is a relatively small player in this particular market, which after all is the world's largest, the sample size as well as size of the funds individual transactions are of a comparable magnitude to well known empirical papers dealing with this issue (Keim and Madhavan [1997], Jones and Lipson [1999]).

We first looked at the estimated costs for transacting. By comparing to the extant literature we found the fund's costs to be on average lower. This may be due to the general lowering of transaction costs in equity markets in later years. Regression analysis showed that many of the same determinants for trading costs were important.

The fund performed their transactions in a particular manner. It first tried to cross as much as possible, using exchanges as "providers of last resort." This allows us to investigate the possibility of adverse selection and missed trading opportunities in these markets. Is it so that the fact that a stock can *not* be crossed is a "good signal" about that particular stock. By doing an event study it seems that there is adverse selection present, the fund may not have gotten the "best stocks" when crossing.

One conclusion to draw from our analysis is that in order to truly measure the costs of trading when using a crossing network it is necessary to properly account for the missed trading opportunities.

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