Informed Trading in Dark Pools

Mahendrarajah Nimalendran — University of Florida

Sugata Ray[1] — University of Florida

Abstract

Using a proprietary high frequency data set, we examine the information in trades originated by different types of traders. We find that the prevalence of informed trading in crossing networks is highest for illiquid stocks traded using algorithms against members of the crossing network, as measured by increased spreads and price impact measures on the quoting exchanges following crossing network transactions. Signed trades on the crossing networks for this particular subset of firms also show the highest momentum going forward over the next 15 to 120 minutes. In contrast, trades for liquid stocks, trades by the crossing network brokerage desk, and members trading large blocks in negotiated crosses contain less information. These results suggest that while crossing networks provide a venue for large block trades to transact with little price impact, they also provide a venue for informed traders to trade, and this information appears to also spill over and provide, price discovery on the quoting exchanges.

JEL Classifications: D53, G12, G28

Keywords: Crossing networks; price discovery; informed trading

July 1, 2011

Comments Welcome

---

[1]Mahendrarajah Nimalendran and Sugata Ray, Warrington College of Business Administration, University of Florida, P.O. Box 117168, University of Florida, Gainesville FL 32611-7168. Nimalendran: mahendrarajah@warrington.ufl.edu; Ray: sugata.ray@ufl.edu.

The authors are grateful to Alfred Berkeley, David Brown, Ian Domowitz, Itay Goldstein, David Musto, Andy Naranjo, Krishna Ramaswamy, Jay Ritter and Wayne Wagner. The authors are also extremely grateful to an undisclosed crossing network for providing the data used in this analysis. Any remaining errors are the responsibility of the authors.

1 Introduction

Crossing networks, or dark pools of liquidity, have come under the spotlight in recent financial press. They account for a large and increasing proportion of shares transacted and the growth they've exhibited over the past few years shows no signs of abating.[2] Along with this growth, there has been increased regulatory scrutiny as well as a surge of academic literature that examines how crossing networks work, why traders use them, and what implications this has for price discovery and market microstructure of the stocks.

SEC's recent "Concept Release on Equity Market Structure," (Release No. 34-61358) has a section which focuses on the "effect of undisplayed liquidity on order execution quality, the effect of undisplayed liquidity on public price discovery, and fair access to sources of undisplayed liquidity." Central to all these concerns is the question we attempt to answer in this study: How much informed trading is there on crossing networks, and how does this affect overall market quality for participants?

Some extant theoretical studies (Buti, Rindi, and Werner (2010a), Zhu (2011), Ye (2009) Hendershott and Mendelson (2000)) examine whether crossing networks attract informed traders trying to garner maximum profit from their information. The papers draw different conclusions based on model parameters and the nature of the information. A number of these studies suggest that informed traders may use crossing networks to reduce their transactions costs and maximize profits from their information. White papers released by crossing networks themselves caution buy-side traders seeking liquidity on crossing networks against "toxic liquidity," referring to executions on crossing networks that are often followed by poor short term returns, suggesting the presence of informed trader counterparties (Mittal (2008) for example). While all these studies posit (either theoretically or empirically) that there is

[2]Rosenblatt Securities reports that 10.86% of volume in July 2011 was on crossing networks that report volumes to them. The TABB Group, a consultancy, estimates the compound annual growth rate (CAGR) of CN volumes at 42.5% over the 2007-2010 horizon.

likely to be some informed trading on crossing networks, without granular data, it is difficult to conclusively show the presence of informed trading.

We use a novel, proprietary data set of transactions on a large crossing network to examine the prevalence of informed trading in crossing networks and its impact on the market microstructure of the stocks traded on the quoting exchanges. We find that informed trading is present, as evidenced by increases in both quoted spreads and price impact measures on the quoting exchanges following transactions on the crossing network. Additionally, positive short term returns to signed trades on the crossing network also suggest the presence of informed traders. These results are strongest for trades involving crossing network members using algorithmic strategies to trade illiquid stocks, as opposed to trades in more liquid stocks, trades manually negotiated by members, and trades executed through the crossing network's brokerage desk. Additionally, the fact that transactions on the crossing network quickly affect characteristics of quoting exchanges (the bid ask spreads and other liquidity measures are significantly affected in as little as 15 minutes) suggests there is price discovery taking place in crossing networks and information is transmitted from the crossing network to the quoting exchange.

Extant recent empirical literature regarding crossing networks include Ready (2009), Weaver (2011), O'Hara and Ye (2009) and Buti, Rindi, and Werner (2010b). Buti, Rindi, and Werner (2010b) provides an excellent survey of the papers and the differences in samples. By and large, these studies relate to the volume on dark pools or market share of dark pools across various securities and explaining these variations. The data used in these samples are characterized by volume aggregation at the daily stock level (an exception is Ready (2009), which aggregates at the monthly level).

Our study uses much more detailed transaction level data that not only provides crossing network volume data, but it also contains (1) high frequency intraday transaction level information with microsecond level timestamps, (2) insight into the mechanism for deriving the transaction price on the crossing network (mid, mid plus "x" pennies or mid minus "x" pennies), which in turn allows us to sign the crossing network trades as buyer or seller driven and (3) descriptions of the broad class of transaction participant for each transaction on the crossing network (regular member, trade against the crossing network brokerage desk, trade generated by algorithms, trade passed through from other dark venues, manually negotiated transactions, etc.).

This is a proprietary, confidential dataset provided by a large crossing network for a representative sample of 100 stocks with a large dispersion in market value. Although relying on one crossing network and a subsample of 100 stocks has its limitations, the granularity from this dataset is invaluable. Further details of the data are found in Section 3.

This paper contributes to the existing empirical literature by using this novel transaction level crossing network data to shed light on the exact nature of trades in crossing networks, and in particular, on the information content of crossing network trades. Additionally, this paper shows that, although informed traders may be able to profit using crossing networks to trade, prices on quoting exchanges adjust relatively quickly to such information. This paper also informs the regulatory debate by showing that there are links between the crossing network and quoting exchanges, and that information from trades on crossing networks quickly transmits through to quoting exchanges.

Naes and Odegaard (2006) is the closest study to ours. That study examines trades by a large buy side trader and finds that executed trades on crossing networks fare worse than orders that were submitted but not executed over a period of 20 trading days. Naes and Odegaard (2006) concludes that informed participants are trading on the crossing networks. Our study builds on this on a number of dimensions:

- Our data is much more recent (2009 vs. 1998). Crossing networks have changed greatly over these 10 years. There are many more trades, and each trade is, on average, much smaller. Additionally, the advent of algorithmic trading has led to algorithms routing fractions of large orders to crossing networks, slowly executing larger orders piecemeal.

- Our data is from a crossing network. This has advantages and disadvantages over data from a large trader. While we cannot determine execution failure as we only have data on successful matches, our data capture trades by various different types of traders, including negotiated member trades (which are similar to the types in the Naes and Odegaard (2006) sample) algorithmic member trades and brokerage desk trades. Empirically, we find these three types of trades have very different characteristics. Our data also includes the pricing mechanism for trades, which allows us to sign trades on the crossing network. We additionally have data on trades in illiquid stocks which the Naes and Odegaard (2006) study does not have, as the trades in their sample involve the Norwegian Government Petroleum Fund acquiring positions in relatively liquid index constituent stocks.

Overall, these differences lead to a more refined set of results than in the Naes and Odegaard (2006)study. We also additionally show the very immediate effects of crossing network transactions on quoting exchanges, suggesting the cumulative abnormal returns measured in days in the Naes and Odegaard (2006) study may have been accelerated by the advent of algorithmic trading and liquidity suites into the order of minutes and hours.

Our study's largest contribution to the theoretical literature is to present empirical findings to refine assumptions underlying theoretical models. Examples of assumptions on which our results have bearing include:

- All of the theoretical studies we know of assume execution at the mid. Our data suggests that a majority of orders execute away from the mid. The ability to specify pricing above and below the mid could help in the price discovery process on the crossing networks.

- A number of (but not all) studies assume that the typical crossing network trader is dealing in large lots. Our results suggest the opposite. While majority of the volume on the crossing network is from relatively few large crosses, almost all the trades (99%) are small and likely to be computer generated.
- No study considers the presences of multiple crossing networks linked through algorithms. Our data suggests more than 90% of trades are crossed in external dark venues.
- In most crossing network models, the choice of trading venues for the informed trader is often modeled through the use of certain parameters (shelf life of the information, ability and cost to trade in the crossing network, nature of the choice of trading venues). Our empirical findings regarding the actual prevalence of informed trading can validate these assumptions. To the extent the assumptions change, the new models can generate better empirical predictions regarding changes in the equilibrium after crossing network introduction.

Our study is less suited to testing the empirical predictions from the theoretical studies. The empirical predictions are largely couched in terms of equilibrium effects relating market characteristics before and after crossing network introduction (see Buti, Rindi, and Werner (2010a) and Hendershott and Mendelson (2000) for example). Given our relatively short (and recent) data time period, it is likely our results will characterize the "after" part of the equilibrium change without providing an adequate characterization before the change.

2 Crossing networks and information

Crossing networks were originally designed as venues where large, uninformed traders could trade large blocks of shares with each other without moving the markets. The quintessential crossing network member was a passive index fund that needed to increase or reduce positions due to inflows or redemptions. The advantage of trading in size at the mid was attractive to these investors, despite uncertain execution prospects.

In recent years, this paradigm has changed greatly. The average size per trade on crossing networks has been decreasing and block trades are becoming less frequent.[3]. Most trades (by frequency) on the crossing networks are now smaller (less than 1000 shares) and likely to be computer generated. Almost all the crossing networks provide a suite of trade management tools which allow their customers to enter simple large orders which are broken down by the algorithm and parsed out over multiple venues across a period of time to minimize price impact. Additionally, many of the restrictions on crossing network membership have been eased, and informed buy side traders who seek trading profits rather than liquidity, such as hedge funds and actively managed mutual funds, have been admitted.

This has led to conditions conducive for information-based algorithmic trading on crossing networks. The nature of the information itself is intricate. In addition to long lived fundamental information, there is trading based on short term fundamental information (e.g. knowledge about an imminent earnings release) as well as short term technical analysis (e.g. short term momentum or reversal strategies). Additionally, there is short term order imbalance-based trading on crossing networks which, while not informed in the traditional sense, relies on order imbalances that move the mid on quoting exchanges to trade at profitable prices on the crossing network.

All of these types of informed trades will leave different footprints in their wake. All are likely to generate positive returns to traders engaging in them. Trades based on fundamental information are also likely to be accompanied by changes in the bid-ask spreads and price impact measures on the quoting exchanges, as this information is disseminated to public. We test for these telltale signs of informed trading in Section 4.

[3]See"The Block Trade is Dying. Long Live Blocks." from Rosenblatt Securities

3 Data

Our data is based on a transaction level dataset from a crossing network for a sample of 100 stocks. This data spans from June 1st 2009 to Dec 31st 2009. The 100 stocks cover a wide range of market capitalizations, industries, liquidity profiles and exchanges. The summary statistics for the 100 stocks covered are presented in Table 1. We merge transaction and quote data from TAQ with transaction data on the crossing network for these tickers to obtain the impact of the crossing network transactions on the quoting exchanges.

The crossing network transaction data is a proprietary, confidential dataset provided by a large crossing network with trade times (at the microsecond level), trade volumes, broad classes of trade counterparties and the derivation process of the trade price from the mid of the NBBO from the quoting exchanges. The data provider is a large crossing network. The average market share of the crossing network by volume for these 100 tickers is about 71 basis points. Rosenblatt securities estimated total crossing network volume at around 8.5% over the course of this sample period. Our crossing network thus constitutes approximately 8.3% of the total fraction of crossing network volume over this period. As a result, we believe that findings regarding crossing network trading from this dataset should be representative of transactions on crossing networks in general.

In our data, there are three principal types of trades/traders on the crossing network. These are the following, along with their shares of volume transacted and number of transactions:

- Trades involving the crossing network's desk (13% of volume, 36% of transactions): Like any other agency, often times a crossing network will "work" large orders for some of the customers on their system.

- Trades involving two large "natural" traders that are manually negotiated (59% of volume, 1% of transactions): The defining characteristics of these types of trades is that they are large and manually negotiated. The average trade size in our sample is around 60,000 shares.

- Trades between members or between a member and external liquidity supplied from another dark venue (28% of volume, 63% of transactions): These trades are generally small and numerous. They are most likely generated by an algorithm that is designed either to minimize transactions costs or to trade for a profit.

Summary statistics for the transactions by counterparty are presented in Table 2. Panels A, B and C provide the total volume, total number of transactions, and average volume per trade, respectively. The columns separate trades by the desk, negotiated member trades, and algorithmic member trades. The rows are internal or external, identifying whether the counterparty to the trade is also a member of the crossing network. Traditional block trades constitute the highest fraction of volume (59%), but only make up 1% of transactions. Algorithmic trades involving members and the brokerage desk constitute the vast majority of trades. Interestingly, except for manually negotiated block trades, the counterparties to more than 90% of these trades are external market participants discovered through various means of communications across multiple dark venues. This suggests that, at least for algorithmic, computer generated crossing network trading, fragmentation worries may be overblown as the search for liquidity has already generated the "trade through" trading mechanism brought about by Reg NMS in the quoting exchanges. This resonates well with findings from O'Hara and Ye (2009) that suggest that current market fragmentation does not harm the price discovery process.

Our data also gives us the pricing mechanism for each transaction on the crossing network. Once a suitable match (a willing buyer and a willing seller for a given quantity of a stock) is found on a crossing network, the network looks to the best bid and best offer on quoting exchanges (or the National Best Bid and Offer, (NBBO)) for pricing the transaction. While most current research largely treats all transactions in crossing networks to be executed at the mid of the NBBO, in actuality, traders are able to specify premiums or discounts vis-a-vis the mid when placing a trade. For example, a motivated buyer may specify an order that promises to pay the mid plus a penny.

One of the fields in our data set contains the method used to derive the pricing from the mid. A histogram of price derivations (in both dollar and percentage terms) is presented in Table 3. We can see that the modal pricing is at the mid, but a sizable fractions of trades are priced above and below the mid. Most derivations away from the mid are at even penny or half penny distances from the mid price. This data allows us to sign trades as buys or sells depending on whether they are priced above or below the mid. Tables 4 presents summary statics showing the distribution of signed trades. Panel A shows the trade volumes, broken out by type of trade on the crossing network over the sample period, as well as whether the trades are executed at the mid, above the mid (signed as "buy" trades) or below the mid (signed as "sell" trades). Panel B shows the number of trades on the crossing network, along with the same breakout in Panel A. Panel C presents the average size per trade. We can see that more of the smaller, computer generated trades (Desk, Member Algorithm) are signed than negotiated member trades, potentially indicating more informational exchange in these smaller trades.

4 Hypotheses and results

Using the data described above, we perform two primary tests for the existence of informed traders on the crossing network:

- We examine the effect of trades on the crossing network on bid ask spreads and price impact measures on the quoting exchange. If crossing network traders are informed, we expect the bid ask spread and price impact to increase subsequent to transactions on crossing networks. This centrally relies on information on crossing network transactions disseminating to other exchanges, and the absence of these results could either indicate lack of informed traders or slower dissemination of information to other exchanges.

- We also examine the returns to signed trades on the crossing network. Recall that while many trades on the crossing network are at the midpoint of the NBBO quotes, a sizable fraction are above or below the mid. We sign trades above the mid as buyer driven (or "buy") trades and trades below as seller driven (or "sell") trades. Informed traders would be more motivated to trade and thus would be more likely to engage in transactions that execute at prices above or below the mid. Additionally, these transactions are likely to generate positive returns going forward. We test for evidence of such positive returns to signed trades.

4.1 Effect of crossing network transactions on market liquidity

There is a rich literature linking bid ask spreads, price impacts and other measures of market liquidity to incidence of informed trading (see for example Kyle (1985) and Glosten and Milgrom (1985)). The effects of informed trading on crossing networks on these measures are less clear.

Zhu (2011) models informed traders with short-lived information choosing between gambling on low price impact, but uncertain, execution on the crossing network and moving the markets with certain executions on quoting exchanges. Their choice will depend on how prevalent and short-lived the information is. In reality, most traders will utilize a combination of crossing network transactions and quoting exchange transactions to maximize executions while minimizing price impact.

This would imply that informed traders on crossing networks are also "working" their trades on the regular quoting exchanges. Thus, one test for the existence of informed trading on the crossing network is to look at the effect of transactions on the crossing networks on bid ask spreads. If there is informed trading on the crossing network, and corresponding informed trading on the quoting exchanges, we would expect bid ask spreads and price impact measures to increase following crossing network transactions.

Table 5 presents the change in the average percentage bid ask spread for the 10 minute period before a transaction to the 10 minute period after the transactions. Panel A presents the changes in the spread by trade type and liquidity profile. Panel B provides the t-statistics for each of the corresponding changes.

We can see that, except for the middle liquidity quintile, there are statistically significant increases in the bid ask spread for all other quintiles. Of these, the greatest magnitude is in the bid ask spread for the most illiquid quintile. The bid ask spread increases by an average of 29.4 bps as a result of the crossing network transaction over the twenty minute horizon. Furthermore, this increase is highest for trades involving the crossing network members' algorithmic trades, although it is still positive and economically and statistically significant for trades involving the brokerage function. Large, negotiated block trades do not significantly affect the quoted bid ask spreads. These results suggest that the prevalence of informed trading on crossing networks is highest by members' algorithmic trades for the most illiquid situations.

As a more formal test of this result, we run a change on change regression of the change in the quoted percentage bid ask spread on the changes in volume, volatility and other controls. These results are presented in Table 6. The regression controls for errors clustered at the ticker level and winsorizes all variables at the 1% level to minimize the effects of outliers. The results are presented for all transactions and subsamples by counterparty. The constant term captures the change in the spread that is unexplained by changes in the volume and volatility. We see that there is a statistically significant increase in the bid ask spread of 1bp for the overall sample. Trades against the desk and negotiated member trades do not have a statistically significant effect on the spread. Algorithmic member trades increase the bid ask spread by 1.4bp each.

In Table 7, we perform the same regression for further segregated samples. Specifically, we create six subsamples of liquid and illiquid situations (where liquid situations are the lowest two ticker periods by percentage bid ask spread, and illiquid situations are the highest two situations by bid ask spread) and segregate the transactions by counterparty. The constant term presents the effects of these transactions after controlling for changes in volume and volatility.

We see that trades against the desk and members' algorithms for illiquid situations leads to statistically and economically significant increases in the bid ask spread. However, the largest increase is for illiquid situations against members' algorithms. The percentage bid ask spread increases by an average of 13.3 bps following each of these transaction on the crossing network, further supporting the hypothesis that such trades are most likely to be informed. Surprisingly, negotiated trades do not increase the bid ask spread. In fact, negotiated trades for liquid situations actually decrease the bid ask spread. This could suggest that such trades are likely to be liquidity driven and successfully conducting a cross for a large number of shares eases the pressure on the quoting exchanges.

Tables 8, 9 and 10 provide the corresponding results for changes in the price impact measure. Price impact is computed as per Amihud (2002), but using minutely intervals. Specifically, the price impact is computed as follows:

$$p_{10} = \sum_{t=1..10} \frac{1}{10} . \frac{|r_t|}{v_t} \tag{1}$$

p_{10} is the price impact measure. $|r_t|$ is the absolute minutely return and v_t is the minutely volume in millions of shares.

The bivariate analysis in Table 8 suggest that almost all types of crossing network transactions increase the price impact on the quoting exchange. However, in the more formal regression results (Table 10), we see once again that the highest statistically significant increase in the price impact is for transactions against members' algorithmic trades in illiquid situations where the price impact goes up by 1.0% per million shares. Interestingly, transactions in illiquid situations against member negotiated trades directionally increases the price impact on the quoting exchanges by more 1.4% per million shares but this is significant only at the 10% level.

Together, we take these findings as evidence of informed trading on the crossing networks, in particular for transactions by members' algorithms for illiquid stocks. Additionally, information regarding the existence of this informed trading is disseminated relatively quickly to the quoting exchanges where relative bid ask spreads and price impacts adjust within the span of minutes.

4.2 Short term returns to signed crossing network transactions

Information possessed by informed traders may be traditional, fundamental information or it may be the result of short term pricing inefficiencies in the crossing networks. Fundamental information may be short or long lived. Our tests primarily focus on short lived information (up to a 2 hour window). Trading based on pricing inefficiencies on the crossing network are short term in nature. For example, a short term order imbalance on the quoting exchanges renders the mid of the best bid and offer higher (lower) than the true fundamental value. In either case, traders who hope to profit on this information can send in a corresponding order to sell (buy) on the crossing network.

While the second definition of informed trading (trades based on pricing inefficiencies on the crossing network) is unlikely to affect bid ask spreads on the quoting exchanges, it will be evident in the returns to signed trades by traders employing such strategies. Along with the effects of traders using short term fundamental information, we would expect the presence of motivated informed traders on crossing networks to result in a positive return to signed trades. If uninformed, liquidity motivated trading were responsible for the signed trades, we would expect the opposite, a short term reversion following trades on the crossing network.

Table 11 presents the short term returns to all trades on the crossing network. Panel A presents the returns to all trades in the sample at various windows (5, 15, 30, 60, 120 minutes), segregated by whether trades are buy, unsigned or sell, along with the returns to the strategy of going long the ‘buys and short the sells. T-stats for each of the returns and the long-short portfolio are also presented. We see that overall, for 15-120 minute horizons, there are significant positive returns to signed trades. Over a 60 minute horizon, going long the buys and shorting the sells generates 13.9 bps of return.

Panels B and C present the same results, but for the most liquid and most illiquid ticker minute quintiles respectively. For the most liquid quintile, we see that the effect is reversed, and the buy-sell portfolio largely generates negative returns. This suggests that signed trading for the most liquid tickers is likely to be liquidity driven. For the most illiquid quintile, the returns are positive and greatly amplified. Over sixty minutes, the buy-sell portfolio generates an economically and statistically significant 520 bps of return.

In an effort to further refine which trades are most susceptible to informed trading for the most illiquid quintile, we further separate the sample into trades against crossing network members and those against the crossing network brokerage desk. These results are presented in Table 12. Panel A presents the results for trades against members and Panel B presents the results for trades against the brokerage desk. We see that the positive return to signed trades is largely confined to trades against members. In fact, returns to the buy-sell portfolio for trades against the desk are largely statistically insignificant and are economically of a much smaller magnitude.

We also estimate a regression model of short term returns (at the 60 minute level) on the derivation of the crossing network transaction price. The results of this regression are presented in Table 13. The regressions control for historical returns and cluster errors at the ticker level. The various columns segregated the sample into trades involving members' algorithms, manually negotiated member traders and trades from the crossing network brokerage desk as well as into liquid and illiquid portions of the sample. The only specification with a significant coefficient on the derivation from the mid (a more refined version of the sign of the trade used earlier), trades against members' algorithms involving ticker minutes in illiquid quintiles. The coefficient of 36.78 can be interpreted as saying for each 1 bp higher than the midpoint a crossing network transaction is, the one hour return is 36 bps higher.

5 Conclusions

Between the increases in bid ask spreads resulting from crossing network transactions and positive returns to signed trades on the crossing network, we conclude that there is information in crossing network trades. Furthermore, these effects are strongest against members' algorithmic trades involving illiquid tickers, suggesting that informed trading is most prevalent for this subset of the sample.

From a practitioner's point of view, these conclusions provide cautionary evidence for traders in crossing networks, echoing sentiments in Mittal (2008) and Naes and Odegaard (2006). From a regulator's point of view, this evidence may be more positive, suggesting relatively speedy dissemination of information from crossing networks to quoting exchanges. In particular, concerns regarding "the effect of undisplayed liquidity on public price discovery" may not be a big concern..

We use proprietary transaction level data shared with us on the condition of confidentiality from a large crossing network. Given the rapidly growing and constantly changing crossing network industry, our results are subject to changing trading strategies and rules at both the crossing network and broader industry level. As a result, further academic research into the effects of crossing networks is warranted. Increased post trade transparency, as contemplated in SEC Proposal No. 34-60997, would be invaluable to continued academic research in the field.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Buti, Sabrina, Barbara Rindi, and Ingrid M. Werner, 2010a, Dark Pool Trading Strategies, *SSRN eLibrary*.

Buti, Sabrina, Barbara Rindi, and Ingrid M. Werner, 2010b, Diving into Dark Pools, *SSRN eLibrary*.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics* 14, 71–100.

Hendershott, Terrence, and Haim Mendelson, 2000, Crossing Networks and Dealer Markets: Competition and Performance, *Journal of Finance* 55, 2071–2116.

Kyle, Albert S, 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315–35.

Mittal, Hitesh, 2008, Are You Playing in a Toxic Dark Pool? A Guide to Preventing Information Leakage, *Journal of Trading* 3, 20–33.

Naes, Randi, and Bernt Arne Odegaard, 2006, Equity trading by institutional investors: To cross or not to cross?, *Journal of Financial Markets* 9, 79–99.

O'Hara, Maureen, and Mao Ye, 2009, Is Market Fragmentation Harming Market Quality?, *SSRN eLibrary*.

Ready, Mark J., 2009, Determinants of volume in dark pools, *Univeristy of Wisconsin, Working Paper*.

Weaver, Daniel G., 2011, Off-Exchange Reporting and Market Quality in a Fragmented Market Structure, *SSRN eLibrary*.

Ye, Mao, 2009, A Glimpse into the Dark: Price Formation, Transaction Cost and Market Share of the Crossing Network, *Cornell University, Working Paper*.

Zhu, Haoxiang, 2011, Do Dark Pools Harm Price Discovery?, *SSRN eLibrary*.

Table 1: Summary statistics of selected tickers

This table presents the summary statistics of the 100 tickers for our sample. Panel A presents the sample distribution across market capitalization deciles. Panel B presents the sample distribution across liquidity deciles, measured by the percentage bid ask spread of each ticker. Panel C presents the sample distribution across listing exchange and Panel B presents the sample distribution across 2 digit SIC codes.

Panel A: Tickers across market capitalization deciles

Mkt cap decile	Frequency	Average MC ($MM)
1	7	2.29
2	8	20.88
3	8	38.25
4	7	80.14
5	8	151.13
6	9	269.78
7	8	533.25
8	6	898.67
9	8	2,011.25
10	31	39,966.68

Panel B: Tickers across bid ask spread deciles

BA Spread decile	Frequency	Pct spread(%)
1	29	0.17%
2	8	0.43%
3	5	0.92%
4	10	1.38%
5	5	2.31%
6	9	3.68%
7	9	5.51%
8	11	7.87%
9	7	12.73%
10	7	19.03%

Panel C: Tickers across listing exchanges

Exchange	Frequency
Arca	4
Amex	35
NASDAQ	35
NYSE	26

Panel D: Tickers across 2 digit SIC code

2 digit SIC code	Frequency
9	1
10	5
12	1
13	8
16	1
20	3
21	2
28	9
29	2
32	1
34	3
35	3
36	8
37	3
38	4
40	1
45	1
48	4
49	4
50	1
51	1
57	1
58	2
59	2
60	4
61	3
63	4
64	1
67	5
73	6
79	1
80	3
87	1
89	1

Table 2: Summary Statistics - Trade participants and counterparties

This table presents the summary statistics over the June 2009 to Dec 2009 period for the variables used. The sample covers trades on the crossing networks(CNs), broken out by whether the trade involves the CN brokerage, members using algorithms or members negotiating large block trades. Summary statistics of total volume, total number of trades and the average size of trade are provided below. These statistics are further broken out by the counterparty to the trades. Counterparties are either outside the member base (external) or one of the members of the CN.

	Volume		
	External	Member	Total
Desk	41,484,271	2,287,900	43,772,171
Member Algo	91,081,923	10,071,100	101,153,023
Member Negotiated	8,469,700	202,541,900	211,011,600
Total	141,035,894	214,900,900	355,936,794
	Number of trades		
	External	Member	Total
Desk	175,532	189	175,721
Member Algo	311,392	388	311,780
Member Negotiated	409	3,087	3,496
Total	487,333	3,664	490,997
	Average Trade size		
	External	Member	Total
Desk	236.33	12,105.29	249.10
Member Algo	292.50	25,956.44	324.44
Member Negotiated	20,708.31	65,611.24	60,358.01
Total	289.40	58,651.99	724.93

Table 3: Summary Statistics - Pricing on the crossing network

This table presents price derivation summary statistics over the June 2009 to Dec 2009 period for transactions on the crossing network. Panel A presents the distribution of deviations from the mid in dollars. Panel B presents the same deviations, expressed as a percentage of the price of the stock, rounded to the nearest 0.1 bp.

Panel A: Derivations from mid (in dollars)

DFM (dollars)	Fraction of transactions (%)
Less than -0.05	0.51
-0.04 to -0.05	0.12
-0.04	0.16
-0.04 to -0.03	0.27
-0.03	0.39
-0.03 to -0.02	0.79
-0.02	1.24
-0.02 to -0.01	3.69
-0.01	10.59
-0.01 to 0	24.99
0.00	36.35
0.00 to 0.01	12.89
0.01	1.96
0.01 to 0.02	0.70
0.02	0.28
0.02 to 0.03	0.15
0.03	0.09
0.03 to 0.04	0.07
0.04	0.04
0.04 to 0.05	0.05
0.05	4.69

Panel B: Derivations from mid (as pct. of stock price)

DFM (rounded to nearest 0.1 bp)	Fraction of transactions (%)
$\leq$ -0.010	0.02
-0.009	0.01
-0.008	0.00
-0.007	0.01
-0.006	0.01
-0.005	0.09
-0.004	0.25
-0.003	0.18
-0.002	0.32
-0.001	6.22
0.000	86.64
0.001	3.67
0.002	1.39
0.003	0.71
0.004	0.15
0.005	0.06
0.006	0.21
0.007	0.02
0.008	0.02
0.009	0.00
$\geq$ 0.010	0.01

Table 4: Summary Statistics - Trade signs and participants

This table presents the summary statistics over the June 2009 to Dec 2009 period for the variables used. The sample covers trades on the crossing networks(CNs), broken out by whether the trade involves the CN brokerage, members using algorithms or members negotiating large block trades. Summary statistics of total volume, total number of trades and the average size of trade are provided below. These statistics are further broken out by derivation of the price of the transaction vis-a-vis the mid of the best bid and best offer. Trades above/below the mid are buyer/seller driven (or "Buy"/"Sell").

	Volume			
	Sell	Unsigned	Buy	Total
Desk	13,375,839	21,559,921	8,836,411	43,772,171
Member Algo	27,397,627	60,339,836	13,415,560	101,153,023
Member Negotiated	10,247,700	190,566,200	10,197,700	211,011,600
Total	51,021,166	272,465,957	32,449,671	355,936,794
	Number of trades			
	Sell	Unsigned	Buy	Total
Desk	76,239	57,070	42,412	175,721
Member Algo	133,446	118,223	60,111	311,780
Member Negotiated	177	3,162	157	3,496
Total	209,862	178,455	102,680	490,997
	Average Trade Size			
	Sell	Unsigned	Buy	Total
Desk	175.45	377.78	208.35	249.10
Member Algo	205.31	510.39	223.18	324.44
Member Negotiated	57,896.61	60,267.62	64,953.50	60,358.01
Total	243.12	1,526.80	316.03	724.93

Table 5: Changes in bid ask spreads following CN transactions

This table presents average changes in the percentage bid ask spread following crossing network transactions and their associated t statistics. The transactions are segregated by counterparty and liquidity quintiles.

Panel A: Change in bid ask spread (%)

	Desk	Negotiated	Member Algo	Total
Most liquid	0.006	0.004	0.016	0.012
2nd quintile	-0.008	-0.020	0.005	0.001
3rd quintile	-0.027	-0.043	-0.005	-0.010
4th quintile	0.014	0.014	0.033	0.026
Least liquid	0.220	0.057	0.315	0.294
Total	0.001	-0.012	0.013	0.009

Panel B: T-statistics associated with the change

	Desk	Member Neg.	Member Algo	Total
Most liquid	18.54	1.44	31.76	37.37
2nd quintile	(10.92)	(5.26)	8.14	2.08
3rd quintile	(12.64)	(3.83)	(3.59)	(8.51)
4th quintile	2.64	0.49	7.39	7.55
Least liquid	6.25	0.28	16.47	17.49
Total	2.14	(2.66)	25.46	24.43

Table 6: Changes in the quoted spread following crossing network transactions

This table presents regression coefficients for the following regression specification: $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δs_{10} is the change in the average quoted percentage spread (best ask minus best bid divided by the mid) ten minutes before a transaction on the crossing network and ten minutes after. The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009. g_i are the explanatory variables, which include changes in volatility and volume for the same time window as well as the market capitalization of the stock. The first column presents results for all transactions. The second, third and fourth columns present the results for trades on the crossing network against the crossing network brokerage desk, negotiated member transactions and algorithmically generated member trades. The t-statistics are computed using standard errors that cluster at the ticker level. +, * and ** denote statistical significance at the 10%, 5% and 1% levels, respectively. All variables are winsorized at the 1% level.

	All	Desk	Member Neg.	Member Algo
Volume change	-0.000**	-0.000*	-0.000+	-0.000*
	(-2.879)	(-2.238)	(-1.757)	(-2.533)
Volatility change	68.399**	49.529**	58.212**	75.595**
	(5.903)	(5.985)	(3.391)	(5.672)
Market cap	-0.000	0.000+	0.000	-0.000
	(-0.706)	(2.013)	(0.945)	(-0.965)
Constant	0.010*	-0.000	-0.007	0.014*
	(2.036)	(-0.115)	(-1.055)	(2.228)
R-squared	0.118	0.086	0.125	0.131
N	225003	78388	1332	145268

Table 7: Changes in the quoted spread for liquid and illiquid situations

This table presents regression coefficients for the following regression specification: $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δs_{10} is the change in the average quoted percentage spread (best ask minus best bid divided by the mid) ten minutes before a transaction on the crossing network and ten minutes after. The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009. g_i are the explanatory variables, which include changes in volatility and volume for the same time window as well as the market capitalization of the stock. The first and second columns presents results for transactions involving against the crossing network brokerage desk, split by whether the transactions occurs in an illiquid or liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Illiquid situations are defined as periods falling in the highest two quintiles of average ticker minute level quoted bid ask percentage spreads. The third and fourth columns present the corresponding results for trades involving negotiated member transactions and the fifth and sixth column presen the results for trades involving algorithmically generated member trades. The t-statistics are computed using standard errors that cluster at the ticker level. +, * and ** denote statistical significance at the 10%, 5% and 1% levels, respectively. All variables are winsorized at the 1% level.

	Liquid desk	Illiquid desk	Liquid Neg	Illiquid Neg	Liquid Algo	Illiquid Algo
Volume change	0.000	-0.006+	0.000	-0.001	-0.000	0.008*
	(0.020)	(-1.787)	(0.429)	(-0.429)	(-0.685)	(2.620)
Volatility change	28.600**	131.536**	16.188*	127.648**	45.438**	127.690**
	(4.318)	(10.378)	(2.236)	(5.337)	(3.227)	(8.729)
Market cap	0.000**	-0.000	0.000	-0.000	-0.000	-0.000+
	(3.678)	(-0.908)	(1.194)	(-1.490)	(-0.737)	(-1.930)
Constant	-0.001	0.048+	-0.008+	0.048	0.008+	0.133*
	(-0.451)	(1.889)	(-1.902)	(0.887)	(1.966)	(2.238)
R-squared	0.070	0.212	0.037	0.287	0.092	0.231
N	66203	4201	906	154	109072	9495

Table 8: Changes in price impact following crossing network transactions

This table presents average changes in the price impact following crossing network transactions and their associated t statistics. The transactions are segregated by counterparty and liquidity quintiles.

Panel A: Change in price impact(% per MM shares)

	Desk	Negotiated	Member Algo	Total
Most liquid	0.04	0.00	0.10	0.07
2nd quintile	0.03	-0.01	0.09	0.07
3rd quintile	0.07	0.05	0.14	0.13
4th quintile	0.14	0.73	0.16	0.16
Least liquid	1.96	3.91	3.37	3.12
Total	0.05	0.12	0.14	0.11

Panel B: T-statistics associated with the change

	Desk	Member Neg.	Member Algo	Total
Most liquid	16.11	(0.20)	28.05	31.80
2nd quintile	7.89	(0.63)	17.79	19.45
3rd quintile	4.60	0.61	12.89	13.69
4th quintile	2.60	2.77	4.08	5.08
Least liquid	5.03	2.34	17.13	17.77
Total	13.41	3.02	32.98	35.66

Table 9: Changes in the price impact following crossing network transactions

This table presents regression coefficients for the following regression specification: $\Delta p_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δp_{10} is the change in the average price impact (as calculated by Amihud (2002), but using minutely intervals and averaging over ten minutes) ten minutes before a transaction on the crossing network and ten minutes after. The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009. g_i are the explanatory variables, which include changes in volatility and volume for the same time window as well as the market capitalization of the stock. The first column presents results for all transactions. The second, third and fourth columns present the results for trades on the crossing network against the crossing network brokerage desk, negotiated member transactions and algorithmically generated member trades. The t-statistics are computed using standard errors that cluster at the ticker level. +, * and ** denote statistical significance at the 10%, 5% and 1% levels, respectively. All variables are winsorized at the 1% level.

	All	Desk	Member Neg.	Member Algo
Volume change	-0.003**	-0.001*	0.001	-0.003*
	(-2.940)	(-2.299)	(0.983)	(-2.630)
Volatility change	488.336**	296.608**	-153.508	567.884**
	(4.097)	(3.578)	(-1.162)	(4.066)
Market cap	-0.000*	-0.000**	-0.000	-0.000
	(-2.079)	(-2.761)	(-1.395)	(-1.547)
Constant	0.153**	0.086**	0.131	0.182**
	(3.690)	(3.936)	(1.494)	(3.209)
R-squared	0.078	0.040	0.012	0.096
N	224903	78329	1331	145228

Table 10: Changes in the price impact for liquid and illiquid situations

This table presents regression coefficients for the following regression specification: $\Delta p_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δp_{10} is the change in the average price impact (as calculated by Amihud (2002), but using minutely intervals and averaging over ten minutes) ten minutes before a transaction on the crossing network and ten minutes after. The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009. g_i are the explanatory variables, which include changes in volatility and volume for the same time window as well as the market capitalization of the stock. The first and second columns presents results for transactions involving against the crossing network brokerage desk, split by whether the transactions occurs in an illiquid or liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Illiquid situations are defined as periods falling in the highest two quintiles of average ticker minute level quoted bid ask percentage spreads. The third and fourth columns present the corresponding results for trades involving negotiated member transactions and the fifth and sixth column presen the results for trades involving algorithmically generated member trades. The t-statistics are computed using standard errors that cluster at the ticker level. +, * and ** denote statistical significance at the 10%, 5% and 1% levels, respectively. All variables are winsorized at the 1% level.

	Liquid desk	Illiquid desk	Liquid Neg	Illiquid Neg	Liquid Algo	Illiquid Algo
Volume change	-0.000	-0.083**	-0.000	-0.042	-0.002+	-0.085*
	(-0.326)	(-3.551)	(-0.277)	(-1.194)	(-1.914)	(-2.144)
Volatility change	113.834**	1117.220**	36.968	-718.504*	340.381*	1070.016**
	(2.891)	(6.889)	(1.483)	(-2.527)	(2.548)	(9.106)
Market cap	-0.000*	-0.000	0.000	-0.000	-0.000	-0.000
	(-2.680)	(-0.694)	(0.599)	(-1.656)	(-1.375)	(-1.653)
Constant	0.047**	0.453*	-0.011	1.399+	0.098**	1.021*
	(3.451)	(2.541)	(-0.416)	(2.035)	(2.884)	(2.075)
R-squared	0.026	0.140	0.002	0.135	0.073	0.185
N	66203	4146	906	153	109065	9473

Table 11: Short term returns to trades on CNs

This table presents short term returns (5, 15, 30, 60 and 120 minute windows) to signed trades on CNs. Trade signs (buy or sell) are determined by the derivation of the trade price vis-a-vis the mid price of the best bid and best offers from the QEs. Derivations above (below) the mid are signed as buyer (seller) driven trades (or buy and sell trades, respectively. Additionally, this table also presents results for most and least liquid tickers separately. Tickers with the lowest (highest) quintile of bid ask percentage spreads and classified as most (least) liquid.

Panel A: All observations

All	5 minutes			15 minutes			30 minutes			60 minutes			120 minutes		
	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N
Sell	1.1	3.35	94,728	1.8	4.78	90,051	-0.4	-1.02	82,562	-2.0	-4.05	73,204	1.6	2.83	60,108
Unsigned	-0.4	-1.49	86,654	0.6	1.90	83,117	-0.3	-0.79	77,146	-1.5	-3.17	67,292	-3.6	-6.65	54,658
Buy	1.7	2.80	48,098	4.5	6.06	45,716	8.2	9.67	42,230	11.9	10.11	35,684	9.2	6.88	28,542
Buy - Sell	0.6	0.85		2.6	3.14		8.6	9.19		13.9	10.89		7.6	5.27	

Panel B: Most Liquid

	5 minutes			15 minutes			30 minutes			60 minutes			120 minutes		
	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N
Sell	2.6	7.12	46,702	0.5	2.14	44,300	1.7	9.33	41,162	3.8	14.48	36,267	8.8	19.43	29,512
Unsigned	0.8	8.00	43,296	2.2	7.04	41,255	0.8	3.92	37,887	0.0	0.12	32,046	0.9	2.01	25,248
Buy	-0.8	-5.26	23,099	-1.0	-3.79	21,667	-0.9	-3.26	20,012	-1.7	-4.39	15,992	-2.6	-4.48	12,498
Buy - Sell	-3.4	-8.62		-1.4	-4.25		-2.6	-7.94		-5.5	-11.65		-11.4	-15.47	

Panel C: Least Liquid

	5 minutes			15 minutes			30 minutes			60 minutes			120 minutes		
	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N
Sell	-32.7	-1.47	1,078	97.1	3.11	885	-101.3	-3.41	810	-19.8	-0.46	663	-79.5	-1.85	493
Unsigned	-64.8	-1.54	440	43.6	0.95	418	7.2	0.16	433	160.6	2.83	388	-6.0	-0.11	334
Buy	68.8	1.38	506	188.4	3.12	480	441.2	6.96	475	500.4	7.72	487	682.2	8.82	406
Buy - Sell	101.5	1.86		91.3	1.34		542.4	7.75		520.2	6.70		761.7	8.61	

Table 12: Short term returns to trades on CNs for low liquidity situations

This table presents short term returns (5, 15, 30, 60 and 120 minute windows) to signed trades on CNs for ticker minutes in the least liquid quintile by percentage bid ask spread, separate by whether the trade is against a CN member or the CN agency desk. Trade signs (buy or sell) are determined by the derivation of the trade price vis-a-vis the mid price of the best bid and best offers from the QEs. Derivations above (below) the mid are signed as buyer (seller) driven trades (or buy and sell trades, respectively.

Panel A: Trades against members

All	5 minutes			15 minutes			30 minutes			60 minutes			120 minutes		
	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N
Sell	-11.5	-0.45	905	143.1	3.96	732	-89.3	-2.61	679	-2.4	-0.05	531	-55.0	-0.98	370
Unsigned	-45.8	-0.80	315	80.2	1.25	297	-20.1	-0.34	313	233.4	3.00	280	-11.4	-0.15	244
Buy	133.5	1.93	360	289.0	3.44	341	638.3	7.51	342	747.1	8.86	355	920.0	9.45	309
Buy - Sell	145.0	1.97		145.8	1.60		727.6	7.94		749.5	7.60		975.0	8.69	

Panel B: Trades against CN desk

	5 minutes			15 minutes			30 minutes			60 minutes			120 minutes		
	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N	Ret(bp)	T-stat	N
Sell	-142.2	-3.54	171	-122.7	-2.50	151	-163.8	-3.34	129	-89.8	-1.40	132	-153.0	-4.30	123
Unsigned	-126.0	-3.47	115	-44.7	-2.10	111	75.6	2.57	110	-37.1	-1.68	98	-2.7	-0.15	82
Buy	-91.7	-3.72	144	-58.3	-2.41	139	-65.9	-2.34	133	-162.9	-4.76	132	-75.1	-2.29	97
Buy - Sell	50.5	1.07		64.4	1.18		97.9	1.73		-73.1	-1.01		77.9	1.61	

Table 13: Short term returns to signed trades on CN

This table presents regression coefficients for the following regression specification: $r_{ttot+60} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $r_{ttot+60}$ is the return over the next 60 minutes and g_i are the explanatory variables. The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009. The explanatory variables include the derivation of the crossing network transaction price from the mid, as a percentage of the stock price and the trailing returns for the past sixty minutes. The first and second columns presents results for transactions involving against the crossing network brokerage desk, split by whether the transactions occurs in an illiquid or liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Illiquid situations are defined as periods falling in the highest two quintiles of average ticker minute level quoted bid ask percentage spreads. The third and fourth columns present the corresponding results for trades involving negotiated member transactions and the fifth and sixth column present the results for trades involving algorithmically generated member trades. The t-statistics are computed using standard errors that cluster at the ticker level. +, * and ** denote statistical significance at the 10%, 5% and 1% levels, respectively. All variables are winsorized at the 1% level.

	Liquid desk	Illiquid desk	Liquid Neg	Illiquid Neg	Liquid Algo	Illiquid Algo
DFM (pct. of price)	6.652	-8.617	349.240	-49.801	-24.824	36.779*
	(0.230)	(-0.500)	(1.241)	(-0.747)	(-0.398)	(2.065)
Returns t-60	0.050	-0.233**	0.062	-0.174	-0.069	-0.242**
	(1.295)	(-4.531)	(0.503)	(-0.992)	(-0.942)	(-6.704)
Constant	-0.029	-0.128*	0.033	0.250	-0.019	-0.088
	(-1.588)	(-2.523)	(0.931)	(1.082)	(-0.599)	(-1.253)
R-squared	0.004	0.064	0.003	0.009	0.008	0.092
N	40170	2509	575	71	65572	5080