# Informational Linkages Between Dark and Lit Trading Venues

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Abstract

We examine the linkages between dark and lit venues using a proprietary data set. We find that algorithmic trades for less liquid stocks lead to higher spreads and price impact, and correlated trading on the lit venues. Also, signed trades for these stocks predict future returns over the next 15 to 120 minutes. Trades for liquid stocks, trades by the dark venue brokerage desk, and members trading large blocks in negotiated crosses transmit less information to the lit venues. The results suggest that dark venues allow informed agents to trade strategically on both venues and facilitate the price discovery process.

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# 1 Introduction

Crossing networks, or dark pools of liquidity, have come under the spotlight in the recent financial press.[2] 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.[3] 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 the market microstructure of the stocks.

The SEC's recent "Concept Release on Equity Market Structure," (Release No. 34-61358) has a section that 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 are the questions we attempt to answer in this study: What is the information content of trades in crossing networks (CN)? Are there linkages between the information in dark pools and information in the lit pools (quoting exchanges)? How does the information contained in the dark pools affect the overall market quality for all market participants?

Some extant theoretical studies (Buti, Rindi, and Werner (2010a), Zhu (2011), Ye (2009) Hendershott and Mendelson (2000)) examine trading strategies of informed and liquidity traders in the presence of CNs and the impact of CNs on price discovery on the quoting exchanges. The papers draw different conclusions based on model parameters and the nature of the information. Hendershott and Mendelson (2000) highlights a number of key factors

[2]We use the term crossing networks and dark pools interchangeably in our study to refer to non-quoting exchanges that facilitate crosses between traders. Once a cross, consisting of a buyer and seller of a fixed quantity of a given ticker, is identified, the crossing network executes and prices the trade using information from the quoting exchange. Traditionally, trades were priced at the midpoint of the best bid and offer, leading to claims of a reduction in transactions costs. The crosses may be continuous or batched at fixed time intervals. For further details on the mechanics of crossing network, see Ready (2009) and Ye (2009).

[3]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. Examples of crossing networks include Posit, SigmaX, Liquidnet, and Instinet.

that determine CN attractiveness (to both informed and liquidity traders) and the effects of CN introduction on market liquidity and the costs borne by liquidity traders. In terms of price discovery on the quoting exchange, Ye (2009) suggests that introducing a "crossing network reduces price discovery and volatility" while Zhu (2011) finds that "adding a dark pool can ... concentrate payoff-relevant information on the exchange, and, under natural conditions, improve the informativeness of exchange prices."

In general, all of these studies admit the possibility 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).

Nonetheless, it is not immediately obvious whether CNs will have high levels of informed trading. Alternative market venues such as regional exchanges and the upstairs market have historically had lower levels of informed trading than the central exchange (see Easley, Kiefer, and O'Hara (1996) and Bessembinder and Venkataraman (2004), for example). Upstairs markets have often been compared to CNs and have kept informed trading at low levels through screening. While CNs historically implemented similar screens to keep out informed traders, recent trends suggest that CNs have become less exclusive and informed traders no longer excluded from the pools.[4] Thus, while it is possible there is some informed trading on crossing networks, without granular data, it has been difficult to quantify the magnitude and economic consequences of such informed trading.

We use a novel, proprietary data set of transactions on a relatively large crossing network to examine the information contained in trades on crossing networks and its impact on the

[4]See section 2 for further details on trends in CN membership and use.

market microstructure of the stocks traded on the quoting exchanges.[5] We find that quoted spreads and price impact measures on the quoting exchanges increase following transactions on the crossing network. The increases are both statistically and economically significant. For example, quoted spreads increase about 10% from base levels. For the overall sample, percentage spreads rises from 10 bp to 11 bp. In addition, we find positive short term returns to signed trades on the crossing network and note that a strategy of going long buyer driven CN trades and short seller driven CN trades generates statistically significant returns of 8.6 bp over a 30 minute horizon.

These effects are greatest for trades involving crossing network members using algorithmic strategies to trade less liquid stocks, as opposed to trades in more liquid stocks, trades manually negotiated by members, and trades executed through the crossing network's brokerage desk. This suggests that information in the crossing networks is concentrated in this sub segment (crossing network members using algorithmic strategies) of the market.

The fact that these effects are seen on the quoting exchanges despite trades on the CN not leaving a traditional "footprint" suggest that either the informed trader on the CN or other informed traders with correlated information are concurrently trading on their information on the quoting exchanges.[6] To examine this conjecture we study the order flow imbalances on the quoting exchange around CN transactions. We find that signed trades on the quoting exchanges around the time of the CN trades are correlated with the direction of the trades on CNs. This is particularly true for signed trades in the least liquid stocks in our sample,

[5]Information, as defined in this study, is broader than the traditional view of information possessed by insiders trading on private fundamental knowledge about their firm. In this study, we consider short term fundamental information, short term technical information (such as following a momentum strategy) as well as crossing network specific trading strategies that selectively place orders on CNs when quoting exchange mid prices are inaccurate representations of the true value of the stock, due to a recent order imbalance on the quoting exchange.

[6]CNs are required to report trades to a trade reporting facilities (TRFs)and the TRFs then report the trades to the consolidated trade data facility. However, it is difficult to identify the exact venue of the trade from TRF reporting. Additionally, it is difficult to see if trades on TRFs are buyer or seller initiated or interacting with liquidity from quoting exchanges. We discuss reporting requirements in further detail in Section 2. Additional details on CN reporting can also be found in Weaver (2011).

where a buyer initiated trade is followed by, on average, 5.75 more minutes with net buy signed trades than sell signed trades. Similarly sell signed trades are followed by 4.22 more sell signed minutes than buy signed minutes. The largest order imbalances are observed in those transactions involving the CN members. These order imbalances are suggestive evidence consistent with concurrent informed trading on the quoting exchange.

These findings suggest that there is informational content in CN trades, particularly for trades involving less liquid stocks by the CN members. This information is integrated with the information in the quoting exchanges, through concurrent trading based on the information on both the dark and lit venues. Finally, the relatively rapid changes in the quoting exchange liquidity measures and prices following CN trades suggest that despite the hidden nature of the information in the CN, price discovery still occurs. This final result may alleviate some of the concerns regarding “the effect of undisplayed liquidity on public price discovery.” noted in the SEC release above.

Extant recent empirical literature regarding crossing networks include Ready (2009), Weaver (2011), O’Hara and Ye (2011) 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 the market share of dark pools across various securities and explain these variations. Ready (2009) finds that independent CNs attract lower volumes for higher dollar bid ask spread stocks, and based on institutional trading patterns, concludes that institutions route such trades to fulfil soft dollar obligations to investment banks for research through commissions. Buti, Rindi, and Werner (2010b) finds that “dark pool activity is concentrated in large firms, stocks with high share volume, high price, low spreads, high depth, and low short-term volatility.” Weaver (2011) and O’Hara and Ye (2011) studies the effect of internalization and fragmentation on overall market quality using trade reporting facility (TRF) data.The data used in these studies 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 other valuable information:

1. High frequency intraday transaction level information with microsecond level timestamps.

2. Transaction price relative to the midpoint of bid/ask spread on the quoting exchange (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. A motivated trader on a crossing network can offer to pay for priority. Similarly, an unmotivated trader may require additional payment for transacting. A motivated buyer may signal he is willing to pay one penny above the mid, and in doing so, get trading priority over all other buyers transacting at the mid. If a seller is found, the motivated buyer's order is filled first, and the seller receives the prevailing mid from the quoting exchange plus a penny for each share traded. Our data provides the derivation mechanism for the pricing of trades, and thus, allow us to sign trades as being driven by the buyer (pricing above the mid) or the seller (below the mid).[7]

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 independent crossing network for a representative sample of 100 stocks, covering the spectrum of stocks over a variety

[7] The ability to sign trades is particularly important for analyzing information in crossing networks. Since the traditional, or modified, calculations of information shares, as posited in Hasbrouck (1995), or Grammig and Peter (2011) requires determining the relationship between returns on the two markets, which would be identical for the CN and quoting exchange, these approaches cannot be used in this study.

of dimensions. 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 study contributes to the existing empirical literature by using this 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 and the mechanism by which it is transmitted to the quoting exchanges. Additionally, we show that, although informed traders may be able to profit using crossing networks to trade, prices on quoting exchanges adjust relatively quickly due to concurrent trading on such information on the quoting exchanges for less liquid stocks. We also inform the regulatory debate mentioned in the SEC concept release on the "effect of undisplayed liquidity on public price discovery" 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 particularly for stocks that have large information asymmetry problems.

Naes and Odegaard (2006) is the closest study to ours. It 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 are much more recent (2009 vs. 1998). Crossing networks have changed greatly over these 11 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 and quoting exchanges, strategically executing larger orders piecemeal to minimize price impact.

- Our data are 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 less liquid 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 the following:

- Many of the theoretical studies (and current conventional wisdom) assume dark pool executions at the midpoint of the bid and ask prices. Our data suggest that a majority of trades 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.

- None of the prior studies we know of considers the presences of multiple crossing networks linked through algorithms. Our data suggest more than 99% of trades are crossed in external dark venues. [8]

- 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 transact 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

[8] Table 5 and Table 2 have details for computing these percentages.

positions due to inflows or redemptions. The advantage of trading large lots of shares 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.[9] 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.[10] Additionally, many of the restrictions on crossing network membership have been eased, and informed buy side traders who seek trading profits as well as liquidity, such as hedge funds and actively managed mutual funds, have been admitted (see "Off-exchange trading: Some like it not," *The Economist* Aug 20 2011.)

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.[11]

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

[10]We will address orders generated by order management suites as algorithmic orders. These orders are different from those generated by algorithms used by high frequency traders (HFT) which have been subject of a number of recent academic studies (see, for example, Hendershott and Riordan (2012) and Menkveld (2011)). While both HFT and liquidity management suites rely on algorithms to generate trades, HFT algorithms often trade in and out of positions rapidly, aiming to capitalize on price discrepancies that resolve within fractions of a second. In contrast, liquidity management suite algorithms aim to parse out trades over time and trading venues, seeking to minimize the transaction costs of executing a large order.

[11]Order imbalance based trading strategies, also referred to as "gaming" strategies, stem from the crossing network prices being derived from the quoting exchanges. A simple method of trading based on this strategy after ascertaining the existence of one sided liquidity, say buy interest in a stock, on the crossing network

Current reporting requirements for trades on CNs facilitate such informed trading. Trades on CNs have to be reported to a trade reporting facility (TRF) within a given time horizon, generally 30 seconds. The TRF then prints the transaction to the tape, but does not identify the venue in which the transaction took place. TRF reported trades include both CN trades as well as trades from non-exchange electronic communication networks (ECNs), such as Lava Flow (Weaver (2011) provides details of the venues reporting to TRFs). Given the lack of venues information, as well as the inability to precisely link quotes to TRF transactions, it is difficult to determine which trades reported by the TRF are executed on CNs, and of those trades, which are executed away from the mid point of the NBBO.

In addition to regulatory reporting, the types of informed trades discussed above will leave different footprints on the quoting exchanges in their wake. In general, all the different types of informed trades 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 as knowledge of this information becomes public. We test for these telltale signs of information in trades on the CN as well as for evidence of information transmission across the CN and the quoting exchanges in Section 4,

# 3 Data

Our data are based on a transaction level dataset from a crossing network for a sample of 100 stocks. Using a merged sample of TAQ, CRSP and Compustat stocks, 100 stocks were picked using stratified sampling to cover a wide range of market capitalizations, industries, liquidity profiles and exchanges. In addition to maintaining broad coverage across all the dimensions, particular attention was paid to the largest (by market capitalization) and most liquid companies. A data request based on these 100 tickers was submitted to the crossing

would be to trade on the quoting exchange in order to increase the mid before trading at this more favorable mid against the buying interest on the crossing network. See Ray (2009) for details of gaming.

network that furnished our data, requesting order and transaction details. The data furnished and used in this study included only transaction level data and spans from June 1st 2009 to Dec 31st 2009. Non-executed order data was not provided to us. The summary statistics for the 100 stocks requested 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 0.52%.[12] Rosenblatt securities estimated total crossing network volume at around 8.9% over the course of this sample period. Our crossing network thus constitutes approximately 5.8% (0.52% / 8.9% = 5.8%) of the total fraction of crossing network volume over this period. This is slightly higher than the expected market share for a leading independent crossing network (the leading independent crossing networks each had about 5% of market share during this period, according to the TABB Group). However, given there is large cross sectional and time series variation in crossing network market shares at the individual stock level, we are not overly concerned by this discrepancy. In general, 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:

[12] We compute this by counting volume where both counterparties are members of the crossing network fully and by discounting volume where only one counterparty is a member of the crossing network by 50%.

- Trades involving the crossing network's desk (13% of volume, 36% of transactions): As opposed to direct trades by the members, the crossing network brokerage desk will "work" orders for large passive traders such as index funds). Ultimately these orders are still member driven, but the brokerage desk has considerable discretion in the order management process.

- 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.[13] This suggests that, at least for

[13] Our data includes transactions where a member of the CN transacts against liquidity on another CN, regardless of which CN the trade was executed on. In computing CN market share earlier, we discount this type of volume at 50%.

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 (2011), which suggest that current market fragmentation does not harm the price discovery process.

We also examine overall market conditions (bid ask spread, volume, volatility) for the 10 minutes before the trade, the 10 minutes after the trade and compare these against the ticker level average across the sample period. The results for this comparison, split by liquidity decile at the time of the crossing network transaction, are presented in Table 3. Panel A presents the average mean values and Panel B presents the average median values. We can see that market conditions surrounding CN transactions are not particularly notable. In fact, consistent with conventional wisdom, CN transactions occur during fairly placid periods (see "Investors Flee Dark Pools as Market Volatility Erupts", Wall Street Journal, Sept 2nd, 2011). Volatility around the time of CN trades is generally lower than average and volumes during these periods are higher. Comparing the mean and the median, we can also see that there are large outliers in a number of these variables. Thus, in multivariate regression analysis, we winsorize all variables at the 1% level to minimize the effects of outliers.

Our data also give 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. This would give this trade priority over all other buy orders on the crossing network, as the other buyers would only be willing to pay the mid.

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 4. 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. These data allow us to sign trades as buys or sells depending on whether they are priced above or below the mid. Table 5 presents summary statics showing the distribution of signed trades across the different types of trades and traders. 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.

## 3.1 Crossing networks: A dark limit order book

The large fraction of trades away from the mid suggest an alternative way to think of crossing networks. The ability to specify pricing preferences, which in turn affect priority, is reminiscent of limit order books. In essence, crossing networks serve as a dark limit order book, within the bounds of the best bid and offer on the quoting exchanges. [14]. Additionally, the crossing network book is a relative book and all pricing is pegged to the mid of the best bid and offer. A visual depiction of this structure is presented in Figure 1.

As such, we would expect many of the theoretical holdings regarding limit order books to be applicable for crossing networks. A trade away from the mid has been characterized as

[14] While trades on the CN may execute away from the mid of the quoting exchanges, they cannot execute outside the bounds of the best bid and best offer on the quoting exchanges without trading through those best bid or offer.

being initiated by a motivated trader. However, it could also be thought of as a result of a wider "spread" within the crossing network, which also supports the view that such trading is driven by informed traders.

# 4 Hypotheses and results

Using the data described above, we perform several tests to measure information content of trades in 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 trades are information driven, 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. We sign trades above the mid as buyer driven (or "buy") trades and trades below as seller driven (or "sell") trades. Information driven trades would be more likely to execute at prices above or below the mid. In addition, these transactions are likely to generate positive returns going forward. We test for evidence of such positive returns to signed trades.

- Finally, we examine the order flow imbalances on the quoting exchange around CN transactions. If the order flow imbalance in the quoting exchange is correlated with signed order flow on the CNs, then it would be indicative of concurrent trading on both venues by the same informed trader for strategic reasons or by other traders with the same piece of information.

## 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 the 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 low price impact with uncertain execution on the crossing network and moving the markets but with certain execution on quoting exchanges. The informed traders' choice will depend on how prevalent and short-lived the information is. Due to the infinitesimal nature of the traders in Zhu's model, each trader's strategy set is binary between the quoting exchange and the crossing network. In aggregate, the informed traders, who possess correlated information, will be distributed between the trading venues based on the parameters of the model. In reality, even most individual 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 (or their similarly informed peers) on crossing networks are also "working" their trades on the regular quoting exchanges. Thus, one test for information based trading on the crossing network is to look at the effect of transactions on the crossing networks on bid ask spreads. [15] If there is information based trading on the crossing network, and existence of this information (but not the actual information itself) becomes known on the quoting exchanges, we would expect bid ask spreads and price impact measures to increase following crossing network transactions.

[15] Note that since CN transactions do not leave the traditional contemporaneous footprints (such as immediate prints on the tape), changes in spread must result from some other information transmission mechanism besides the liquidity providers on the quoting exchanges observing the CN transactions. We posit that this mechanism is via concurrent trading on the quoting exchanges by the informed trader or other traders with correlated information but we are unable to identify the exact conduit.

Table 6 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.[16] 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 there are statistically significant increases in the bid ask spread for every quintile except the middle liquidity quintile. Of these, the greatest magnitude is in the bid ask spread for the least liquid quintile. The bid ask spread increases by an average of 29.4 bp on a base spread of 5.185%, or an increase of 5.7% (0.294/5.185= 5.7%) 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 where the spread increases by 31.5bp (or a 6.1% increase). We also note that the fourth liquidity quintile also has a significant increase 0.033 over the base spread of 1.048%, or an increase of about 3.1%. The increases in spread are also positive and economically and statistically significant (although slightly lower in magnitude) 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 information driven trading on crossing networks is highest for members' algorithmic trades for the least liquid stock transaction.

As a more formal test of this result, we estimate 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 7. 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.

[16] Horizons used in this study include the t-10 to t+10 horizon used in studying changes in spreads and returns over the t+5 to t+120 horizon. This is in contrast with time horizons used in some algorithmic trading studies, such as Hasbrouck and Saar (2011) and Menkveld (2011), which focus on time horizons in milliseconds and seconds, respectively. Since trades on our CN are not immediately visible on QE and any effects these trades may have are dependent on concurrent/subsequent trading on quoting exchanges, we feel our study is better conducted with a longer time horizon. Consistent with this view, when examining short horizon returns below 15 minutes, we find that noise eliminates the significance of our findings.

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 on a base spread of 0.103%, or an increase of 13.6%.

In Table 8, we perform the same regression for further segregated samples. Specifically, we create six subsamples of liquid and less liquid situations (where liquid situations are the lowest two quintiles of ticker periods by percentage bid ask spread, and less liquid situations are the highest two quintiles 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 by the crossing network brokerage desk and members' algorithms for less liquid situations leads to statistically and economically significant increases in the bid ask spread. Algorithmic trades by members in liquid tickers also have significant effects on the spread, although the magnitude is smaller. The largest increase is for least liquid situations by members' algorithms. The percentage bid ask spread increases by an average of 13.3 bps following each of these transactions 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 9, 10 and 11 provide the corresponding results for changes in the price impact measure. Price impact is computed as per Amihud (2002), but using minute 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 return per minute and $v_t$ is the volume per minute in millions of shares.

The bivariate analysis in Table 9 suggest that almost all types of crossing network transactions are associated with increases in the price impact on the quoting exchange. However, in the more formal regression results (Table 11), we see once again that the highest statistically significant increase in the price impact is for transactions against members' algorithmic trades in less liquid securities where the price impact goes up by 1.0% per million shares. Interestingly, transactions in less liquid situations against member negotiated trades directionally increases the price impact on the quoting exchanges by more 1.4% per million shares and is significant at the 10% level. While we compute all price impact sensitivities as responses to transactions of a million shares, the average 10 minute volume for stocks in the lower liquidity situations is between 2000 and 5000 shares (see Table 3). Prices impacts from these more modest volumes would be correspondingly lower.

The findings reported above provide evidence of information based trading on the crossing networks, in particular for transactions by members' algorithms for less liquid stocks. Further, knowledge 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

The information driving these trades on CNs 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 is short term in nature. For example, a short term order imbalance due to an excess of buys on the quoting exchanges renders the mid of the best bid and offer higher than the true fundamental value. Traders who hope to profit on this information can send in a corresponding order to sell 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 12 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 shorting 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 5 minutes, we find positive returns though they are not statistically significant. Over a 30 minute horizon, going long the buys and shorting the sells generates 8.6 bp of return.

This table also presents a comparison of transaction costs on the quoting exchanges by computing a hypothetical "VWAP slippage". The last column presents the mean value weighted average price slippage if the signed transaction is conducted on the quoting exchange. The slippage is computed as the volume weight average price (VWAP) on the quoting exchange until the volume requirement is met minus the mid point of the NBBO at the time of the CN trade. [17] We use the VWAP for the first 1000 shares transacted on the quoting exchange after the CN transaction for all CN transactions below 1000 shares and the VWAP for 5000 shares for all CN transactions between 1000 and 5000 shares. If the required transaction level is not reached within 60 minutes, we do not compute this measure. The computed VWAP is compared to the mid point of the NBBO on the quoting exchanges to obtain the slippage number. We do not compute this measure for transactions above 5000 shares as routing such large orders to the quoting exchanges would likely significantly change the existing market dynamics. This slippage could be thought of as either the transaction cost for a signed trade that would have been routed to the quoting exchange instead or as a measure of the transaction cost of the quoting exchange alternative. Note that since we cannot know how the markets would have reacted to additional order flow on the quoting exchanges, this is purely a hypothetical estimate, but is presented for comparison purposes. The numbers suggest that (1) fills are available on the quoting exchange for almost all small orders on the crossing network and, (2) the computed slippage numbers are small relative to losses to informed traders on the CN.

Panels B and C present the same results, but for the most liquid and least liquid 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 least liquid quintile, the returns are positive and greatly amplified. Over thirty minutes, the buy-sell portfolio generates an economically and statistically significant 542.4 bps of return. The slippage numbers are larger here, but are still much smaller than the returns to the information

[17] This analysis is similar in spirit to Kryzanowski and Zhang (2002), where the authors attempt to compare the per share execution price across two markets for the same security. Since we do not have the luxury of a matched pair of transactions in separate market venues, we compute hypothetical transaction costs for a CN order had it instead been routed to the quoting exchange using extant execution data on the quoting exchanges.

based trades. [18]

In an effort to further refine which trades are most susceptible to informed trading for the least liquid quintile, we further separate the sample into trades by crossing network members and those by the crossing network brokerage desk. These results are presented in Table 13. 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 30 minute level) on the sign of the trade on the crossing network. The results of this regression are presented in Table 14. The dependent variable is the return over the next thirty minutes and the independent variable is the sign of the trade (trades above the mid are signed as a +1, trades below the mid are signed as a -1 and trades at the mid are signed as a 0). The regressions control for historical returns and cluster errors at the ticker level. The various columns segregate 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 less liquid groups of the sample. The only specification with a significant coefficient on the sign of the trade involves trades by members' algorithms involving less liquid securities. The coefficient of 0.097 can be interpreted as signed trades outperforming unsigned trades by 9.7bp over the next thirty minutes. [19]

[18] While these returns are extremely large, the bid ask spreads and price impact numbers for these illiquid situations is fairly large (1-6% bid ask spread; see Table 3). This in conjunction with the our argument that these signed trades are part of a broader order execution algorithms that split orders between lit and dark exchanges explain the large returns to the signed trades. It is important to note that due to transactions costs, a trader would not be able to generate this return trading along with signed dark volumes as transactions costs would significantly reduce the realized returns.

[19] This number is significantly lower than the returns to the signed portfolios presented above(500-750bps, see Table 12 and Table 13). This is because controlling for historical returns accounts for much of the correlated trading leading the price movements seen earlier. However, the signed dark trades do still have

### 4.3 Quoting exchange order flow surrounding CN transactions

In previous sections we posit that information driven trading in dark pools is accompanied by traders with similar information trading on quoting exchanges, thus leading to the increased quoted spreads and positive returns to signed trades. In order to test for the existence of such concurrent trading, we examine order flow imbalances on the quoting exchange around CN transactions. The result of this analysis is presented in Table 15.

We observe that in general, signed trades on the CN are sandwiched by similarly signed trades on the quoting exchange. This is particularly true for signed trades in the least liquid situations (Panel C), where a buyer initiated trade is followed by, on average, 5.75 more minutes with net buy signed trades and sell signed trades. Similarly sell signed trades are followed by 4.22 more sell signed minutes than buy signed minutes. When splitting the least liquid situations into those involving the CN members and the CN desk, we see once again that the largest order imbalances are observed in those transactions involving the CN members.

These order imbalances provide evidence consistent with concurrent informed trading on the quoting exchange. Such order imbalances will lead to the short term returns and increased spreads observed above. However, the existence of these order imbalances does not rule out information leakage from a purely reporting based perspective. As highlighted in Section 2, CN trades are reported, albeit without trade venue and signing information, through trade reporting facilities. It is possible that CN trades and their signs can be identified through diligent parsing of TRF trades and the effects seen on the CN are a result of such reporting rather than the effects of concurrent trading.

some predictive power. In general, these results are consistent with trades on dark pools being part of a larger order execution strategy that also utilizes lit exchanges.

## 4.4 Using earnings days to identify the nature of informed trading on CNs

We highlighted four different types of information that traders may possess: (1) Long term, fundamental information, (2) Short term fundamental information, (3) Short term technical information, and (4) CN specific pricing mechanism arbitrage strategies. Given the short time horizons considered in this paper, tests in the previous sections are more likely to uncover (2), (3) and (4).

To check for trading based on fundamental information, we perform the tests documented above for the subsample of earning release days. If short term fundamental information is driving the results, we would expect the results to be stronger for this subset of days. Results for these tests are presented in Table 16. Panel A presents the results corresponding to Table 8 and Panel B presents the results corresponding to Table 14. Although a number of the specifications do not have enough observations to estimate, we can see that spreads do not increase significantly following crossing network transactions. Neither do signed trades on the crossing network yield significant returns.

These results suggest that the information possessed by traders on the crossing network is unlikely to be short term fundamental information related to earnings releases and informed traders on crossing networks are more likely to using be short term technical strategies and short term crossing network pricing arbitrage strategies. This is also consistent with the algorithmic nature of the crossing network trades we focus on.

It remains puzzling how such high returns to informed trading persist in the CN. Given the relatively low frequency of less liquid ticker transactions, it is possible that traders find it difficult to learn from their adverse executions. It is also possible that some algorithms seeking execution on CNs inherently perform worse than others. Anand, Irvine, Puckett, and Venkataraman (2011) document and study such discrepancies in the brokerage space, finding that " institutions that are skilled in their trade executions can maintain their relative advantage over time." It is plausible that superior algorithms are similarly able to generate persistent positive returns.

## 4.5 Discussion of alternative explanations

While we have couched our interpretation of the results in this paper in terms of information in CNs and links between information in CNs and quoting exchanges through concurrent trading, an alternative explanation for these findings (increasing spreads following CN transactions, superior performance of signed CN trades and concurrent signed trading on quoting exchanges) could involve a large trader trading an illiquid security, combined with limited inventory held by market makers and slow replenishment of the inventory. We offer two resolutions towards disentangling these explanations.

First, we believe it is unlikely that this is the primary explanation for our findings because trades on the CN that lead to this result are relatively small (the average trade size is about 300 shares, from Table 2. Furthermore, the average market conditions around these trades generally show less volume than regular market conditions (see Table 3). Finally, the fact the superior returns on signed trades persist for up to 2 hours suggests that there is a persistent component in these returns (see Tables 12 and 13).

Second, we recognize that, in a broad sense, our definition of information would include such scenarios involving a large trader of an illiquid security. Such a trader has private information about the stock (the fact that she herself is trying to buy or sell a large quantity of it). Our results, currently presented in terms of trading based on short term fundamental and technical information, could easily be recast in terms of reducing transactions costs for a large, but otherwise uninformed, trader. The hypothetical VWAP measures presented in Tables 12 and 13 both suggest that trading on the quoting exchanges as opposed to the CN would increase transactions costs for the large, uninformed trader (in the case of trades by member algorithms in less liquid situations, motivated buyer (seller) driven trades will outperform the hypothetical quoting exchange VWAP by 15.0bp (19.9bp)). The large, uninformed trader's knowledge that she is trading in size is valuable information and while she does not profit from this information, she does minimize costs when trading on the CN based on this information.

# 5 Conclusions

Based on the increases in bid ask spreads resulting from crossing network transactions and large, statistically significant, positive returns to signed trades on the crossing network, we conclude that there is information in crossing network trades. Such information is short term in nature and is more likely to be technical rather than fundamental. Furthermore, these effects are strongest for members' algorithmic trades involving less liquid securities. We also provide some evidence that the information in signed CN trades are correlated with the net trade volume on the quoting exchanges around the CN trade for the less liquid securities. This is consistent with the correlated trading hypothesis that informed traders use both the CNs and quoting exchanges to trade strategically.

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). Liquidity seekers looking for fills from CNs for less liquid stocks may face potential losses from executions against more informed counterparties. These losses are substantially larger than estimated execution costs on a VWAP basis using subsequent quoting exchange executions. 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, this would reduce concerns regarding "the effect of undisplayed liquidity on public price discovery."

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.

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Figure 1: Crossing Network: A Limit order book within a limit order book

Crossing networks act as a limit order book within the bounds of the quoted limit order book. The crossing network is pegged to the mid point of the quoting exchange and traders can specify their prices relative to that mid. In this case, there are more motivated sellers than buyers on the crossing network, leading to the best offer on the crossing network being slightly below the mid. However, the orders on the crossing network are not publicly visible and do not affect the best bid and offer on the quoting exchanges. While trades on the CN may execute away from the mid of the quoting exchanges, they cannot execute outside the bounds of the best bid and best offer on the quoting exchanges without trading through the best bid or offer on the quoting exchange.

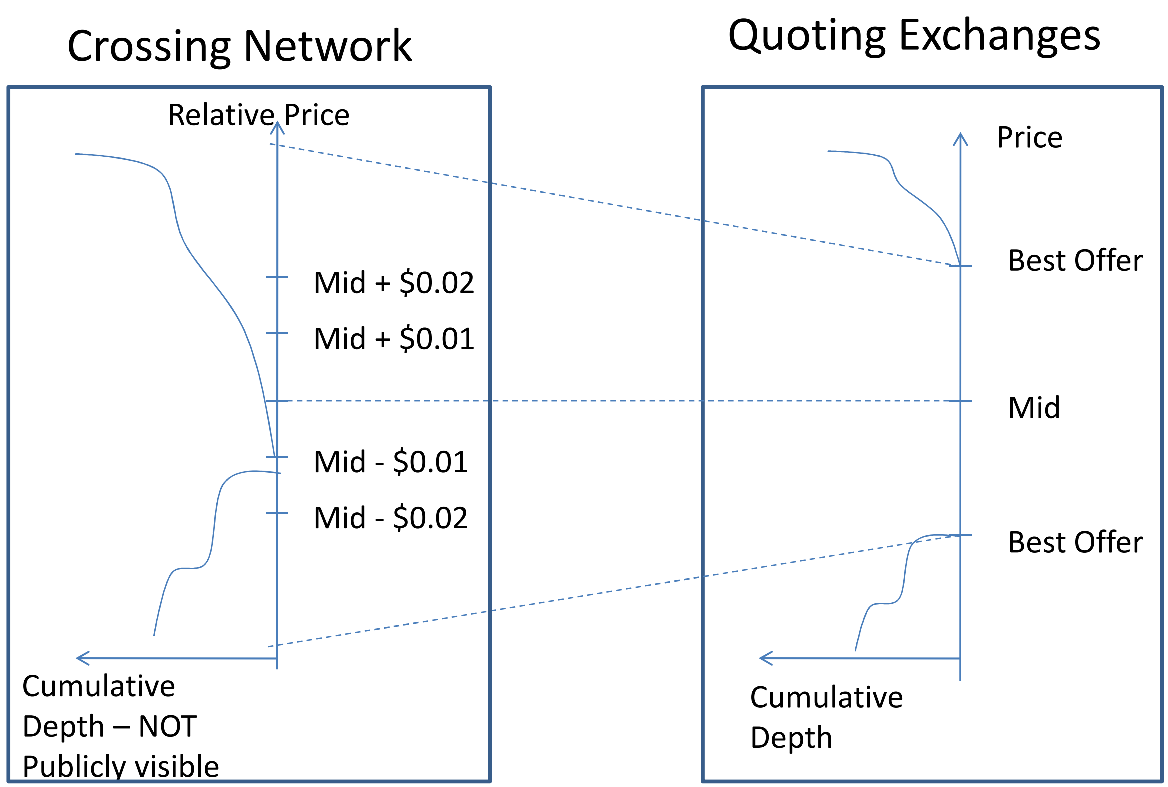

Table 1: Summary statistics of selected tickers

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 (most liquid) | 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 (least liquid) | 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 total volume, total number of trades and the average size of trade for our sample of trades on the crossing networks over the June 2009 to Dec 2009 period. The statistics are broken out by whether the trade involves the crossing network brokerage, members using algorithms or members negotiating large block trades. 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 crossing network.

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: Market conditions summary

This table presents the mean and median market conditions (relative bid ask spread, return volatility and volume) for the 10 minutes before and after crossing network transactions, split by liquidity quintile, compared ticker level market conditions. Panels A and B present the mean and median market conditions, respectively. Each market characteristic (relative bid ask spread, volatility and volume) is examined over the entire sample period (the first column, "Avg." as well as before and after the CN transactions (second and third column in each set). The first three columns examine the relative bid ask spreads. Bid ask spread is first computed at the ticker mute level by using size weighted bid and ask prices. The difference between the ask and the bid is divided by the mid of the ask and the bid to compute the relative bid ask spread. The average of this number is computed for ten minute periods before and after each CN transaction. The average ticker level spread ("Avg.") is computed as the average of all the computed bid ask spreads for all 10 minute periods. The second three columns examine the volatility. Volatility is computed as the standard deviation of minutely returns over the ten minutes before and after each CN transaction. The average ticker level volatility is the average of all computed volatilizes for all 10 minute windows for each ticker. The last three columns examine quoting exchange trading volume. The volume is computed as the average minutely volume for the 10 minutes before and after each CN transaction. The average ticker level volume is the average of all computed volumes for all 10 minute windows for each ticker. These characteristics are then aggregated over all tickers in each liquidity quintile to compute the mean or median.

Panel A: Mean market conditions

| | Bid Ask Spread | | | Volatility | | | Volume | | |
|---|---|---|---|---|---|---|---|---|---|
| Liq. quintile | Avg | Before | After | Avg | Before | After | Avg | Before | After |
| 1 | 0.160 | 0.088 | 0.104 | 0.195 | 0.028 | 0.036 | 43,080 | 55,436 | 56,862 |
| 2 | 0.239 | 0.192 | 0.196 | 0.579 | 0.102 | 0.043 | 16,014 | 25,039 | 26,321 |
| 3 | 0.388 | 0.485 | 0.484 | 1.673 | 0.110 | 0.447 | 8,280 | 11,801 | 13,621 |
| 4 | 0.948 | 1.174 | 1.203 | 10.041 | 0.372 | 25.22 | 5,169 | 5,759 | 9,342 |
| 5 | 3.414 | 5.183 | 5.798 | 33.973 | 12.556 | 12.196 | 2,196 | 3,452 | 2,619 |
| Total | 0.296 | 0.283 | 0.307 | 1.444 | 0.194 | 1.665 | 27,437 | 37,067 | 38,286 |

Market conditions summary cont'd

Panel B: Median market conditions

| | Bid Ask Spread | | | Volatility | | | Volume | | |
|---|---|---|---|---|---|---|---|---|---|
| Liq. quintile | Avg | Before | After | Avg | Before | After | Avg | Before | After |
| 1 | 0.124 | 0.070 | 0.070 | 0.047 | 0.020 | 0.020 | 21,702 | 28,442 | 30,751 |
| 2 | 0.217 | 0.155 | 0.150 | 0.077 | 0.028 | 0.027 | 11,056 | 10,662 | 11,113 |
| 3 | 0.283 | 0.424 | 0.403 | 0.120 | 0.049 | 0.046 | 6,614 | 6,181 | 6,147 |
| 4 | 0.413 | 0.885 | 0.885 | 0.964 | 0.057 | 0.055 | 4,356 | 3,155 | 3,408 |
| 5 | 3.824 | 3.725 | 4.278 | 2.825 | 0.040 | 0.050 | 1,623 | 1,729 | 1,033 |
| Total | 0.191 | 0.115 | 0.117 | 0.077 | 0.027 | 0.027 | 11,375 | 13,416 | 13,912 |

Table 4: Summary Statistics - Pricing on the crossing network

This table presents the summary statistics of price deviations from the mid for our sample of trades on the crossing networks over the June 2009 to Dec 2009 period. Panel A presents the distribution of deviations from the mid of the best bid and offer prices 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 (%) |
|---|---|
| -0.05 or less | 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 or more | 4.69 |

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

| DFM (% rounded to nearest bp) | Fraction of transactions (%) |
|---|---|
| $\leq$ -0.10 | 1.96 |
| -0.09 | 0.38 |
| -0.08 | 0.58 |
| -0.07 | 0.87 |
| -0.06 | 2.81 |
| -0.05 | 1.24 |
| -0.04 | 3.73 |
| -0.03 | 6.70 |
| -0.02 | 9.44 |
| -0.01 | 12.92 |
| 0.00 | 38.68 |
| 0.01 | 6.34 |
| 0.02 | 3.53 |
| 0.03 | 3.63 |
| 0.04 | 0.83 |
| 0.05 | 0.19 |
| 0.06 | 0.44 |
| 0.07 | 0.78 |
| 0.08 | 0.39 |
| 0.09 | 0.04 |
| $\geq$ 0.10 | 4.52 |

Table 5: Summary Statistics - Trade signs and participants

This table presents the summary statistics of total volume, total number of trades and the average size of trade for our sample of trades on the crossing networks over the June 2009 to Dec 2009 period. The statistics are broken out by whether the trade involves the crossing network brokerage, members using algorithms or members negotiating large block trades. 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 6: Changes in bid ask spreads following crossing network 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 presents the numerical changes in the percentage bid ask spread along with the base average relative bid ask spread for each quintile and Panel B presents the corresponding t statistics for the changes. For example, for the overall sample, bid ask spreads go up by 0.9 bp following a crossing network transactions on a base bid ask spread of 10.3 bp and the t statistic associated with this increase is 24.43. All figures in Panel A are significant at the 5% level except those marked with (NS).

Panel A: Average change in bid ask spread (%)

| | Desk | Negotiated | Member Algo | All | Base Spread |
|---|---|---|---|---|---|
| Most liquid | 0.006 | 0.004(NS) | 0.016 | 0.012 | 0.061 |
| 2nd quintile | -0.008 | -0.020 | 0.005 | 0.001 | 0.151 |
| 3rd quintile | -0.027 | -0.043 | -0.005 | -0.010 | 0.447 |
| 4th quintile | 0.014 | 0.014(NS) | 0.033 | 0.026 | 1.048 |
| Least liquid | 0.220 | 0.057(NS) | 0.315 | 0.294 | 5.185 |
| Total | 0.001 | -0.012 | 0.013 | 0.009 | 0.103 |

Panel B: T-statistics associated with the change

| | Desk | Member Neg. | Member Algo | All | Base Spread |
|---|---|---|---|---|---|
| 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 7: 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 $\Delta s_{10}$ is the change in the average quoted percentage spread (best ask minus best bid divided by the mid multiplied by 100) 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 to reduce the effect of outliers.

| | All | Desk | Member Neg. | Member Algo |
|---|---|---|---|---|
| Volume change (MM shares) | -0.194** | -0.131* | -0.217+ | -0.209* |
| | (-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 (BN) | -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 8: Changes in the quoted spread for liquid and less liquid situations

This table presents regression coefficients for the following regression specification: $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $\Delta s_{10}$ 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 a liquid or less liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Less liquid 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 to reduce the effect of outliers.

| | Desk | | Negotiated | | Algo | |
|---|---|---|---|---|---|---|
| | Liquid | Less liquid | Liquid | Less liquid | Liquid | Less liquid |
| Volume change (MM) | 0.001 | -5.806+ | 0.028 | -1.453 | -0.062 | 7.899* |
| | (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 (BN) | 0.000** | -0.001 | 0.000 | -0.005 | -0.000 | -0.005+ |
| | (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 9: 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. Panel A presents the numerical changes in the price impact measure for each quintile and Panel B presents the corresponding t statistics for the changes. The transactions are segregated by counterparty and liquidity quintiles.

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

| | Desk | Negotiated | Member Algo | All |
|---|---|---|---|---|
| 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 | All |
|---|---|---|---|---|
| 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 10: 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 $\Delta p_{10}$ is the change in the average price impact (as calculated by Amihud (2002), but using ten minutely intervals and averaging over the 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 to reduce the effect of outliers.

| | All | Desk | Member Neg. | Member Algo |
|---|---|---|---|---|
| Volume change (MM shares) | -2.655** | -1.330* | 0.856 | -3.233* |
| | (-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 (BN) | -0.000* | -0.000** | -0.001 | -0.001 |
| | (-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 11: Changes in the price impact for liquid and less liquid situations

This table presents regression coefficients for the following regression specification: $\Delta p_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $\Delta p_{10}$ 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 a liquid or less liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Less liquid 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 to reduce the effect of outliers.

| | Desk | | Negotiated | | Algo | |
|---|---|---|---|---|---|---|
| | Liquid | Less liquid | Liquid | Less liquid | Liquid | Less liquid |
| Volume change (MM) | -0.124 | -82.639** | -0.074 | -41.849 | -1.623+ | -85.249* |
| | (-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 (BN) | -0.000* | -0.004 | 0.000 | -0.087 | -0.000 | -0.033 |
| | (-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 12: Short term returns to trades on crossing networks

This table presents short term returns (5, 15, 30, 60 and 120 minute windows) to signed trades on the crossing network. 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 quoting exchanges. Derivations above (below) the mid are signed as buyer (seller) driven trades (or buy and sell trades, respectively. The final columns also present the mean value weighted average price slippage if the signed transaction is conducted on the quoting exchange, expressed as a percentage of the starting mid price. This is computed by using the VWAP for the first 1000 shares transacted on the quoting exchange after the CN transaction for all CN transactions below 1000 shares and the VWAP for 5000 shares for all CN transactions between 1000 and 5000 shares. If the required transaction volume level is not reached within 60 minutes, we do not compute this measure. We do not compute this measure for transactions above 5000 shares. Additionally, this table also presents results for most and least liquid quintiles of tickers separately with liquidity measured as the percentage bid ask spread.



Panel A: All observations

| | 5 minutes | | 15 minutes | | 30 minutes | | 60 minutes | | 120 minutes | | VWAP slippage | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat |
| Sell | 1.1 | 3.35 | 1.8 | 4.78 | -0.4 | -1.02 | -2.0 | -4.05 | 1.6 | 2.83 | -0.4 | -10.90 |
| Unsigned | -0.4 | -1.49 | 0.6 | 1.90 | -0.3 | -0.79 | -1.5 | -3.17 | -3.6 | -6.65 | -0.1 | -2.61 |
| Buy | 1.7 | 2.80 | 4.5 | 6.06 | 8.2 | 9.67 | 11.9 | 10.11 | 9.2 | 6.88 | 0.5 | 11.05 |
| 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 Quintile

| | 5 minutes | | 15 minutes | | 30 minutes | | 60 minutes | | 120 minutes | | VWAP slippage | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat |
| Sell | 2.6 | 7.12 | 0.5 | 2.14 | 1.7 | 9.33 | 3.8 | 14.48 | 8.8 | 19.43 | 0.1 | 4.54 |
| Unsigned | 0.8 | 8.00 | 2.2 | 7.04 | 0.8 | 3.92 | 0.0 | 0.12 | 0.9 | 2.01 | 0.1 | 3.71 |
| Buy | -0.8 | -5.26 | -1.0 | -3.79 | -0.9 | -3.26 | -1.7 | -4.39 | -2.6 | -4.48 | 0.3 | 9.59 |
| 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 Quintile

| | 5 minutes | | 15 minutes | | 30 minutes | | 60 minutes | | 120 minutes | | VWAP slippage | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat |
| Sell | -64.8 | -1.54 | 97.1 | 3.11 | -101.3 | -3.41 | -19.8 | -0.46 | -79.5 | -1.85 | -19.1 | -18.04 |
| Unsigned | 68.8 | 1.38 | 43.6 | 0.95 | 7.2 | 0.16 | 160.6 | 2.83 | -6.0 | -0.11 | -4.9 | -2.62 |
| Buy | -14.3 | -0.73 | 188.4 | 3.12 | 441.2 | 6.96 | 500.4 | 7.72 | 682.2 | 8.82 | 8.1 | 4.51 |
| Buy - Sell | 50.5 | 1.09 | 91.3 | 1.34 | 542.4 | 7.75 | 520.2 | 6.70 | 761.7 | 8.61 | | |

Table 13: Short term returns to trades on the crossing network for low liquidity situations

This table presents short term returns (5, 15, 30, 60 and 120 minute windows) to signed trades on the crossing network for ticker minutes in the least liquid quintile by percentage bid ask spread, separate by whether the trade is against a crossing network member or the crossing network 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 quoting exchanges. Derivations above (below) the mid are signed as buyer (seller) driven trades (or buy and sell trades, respectively. The final columns also present the mean value weighted average price slippage if the signed transaction is conducted on the quoting exchange, expressed as a percentage of the starting mid price. This is computed by using the VWAP for the first 1000 shares transacted on the quoting exchange after the CN transaction for all CN transactions below 1000 shares and the VWAP for 5000 shares for all CN transactions between 1000 and 5000 shares. If the required transaction volume level is not reached within 60 minutes, we do not compute this measure. We do not compute this measure for transactions above 5000 shares.

Panel A: Trades by members

| | 5 minutes | | 15 minutes | | 30 minutes | | 60 minutes | | 120 minutes | | VWAP slippage | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat |
| Sell | -11.5 | -0.45 | 143.1 | 3.96 | -89.3 | -2.61 | -2.4 | -0.05 | -55.0 | -0.98 | -19.9 | -17.92 |
| Unsigned | -45.8 | -0.80 | 80.2 | 1.25 | -20.1 | -0.34 | 233.4 | 3.00 | -11.4 | -0.15 | -1.7 | -0.77 |
| Buy | 133.5 | 1.93 | 289.0 | 3.44 | 638.3 | 7.51 | 747.1 | 8.86 | 920.0 | 9.45 | 15.0 | 7.86 |
| 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 by crossing network agency desk

| | 5 minutes | | 15 minutes | | 30 minutes | | 60 minutes | | 120 minutes | | VWAP slippage | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat | Ret(bp) | T-stat |
| Sell | -142.2 | -3.54 | -122.7 | -2.50 | -163.8 | -3.34 | -89.8 | -1.40 | -153.0 | -4.30 | -11.6 | -3.37 |
| Unsigned | -126.0 | -3.47 | -44.7 | -2.10 | 75.6 | 2.57 | -37.1 | -1.68 | -2.7 | -0.15 | -14.9 | -4.51 |
| Buy | -91.7 | -3.72 | -58.3 | -2.41 | -65.9 | -2.34 | -162.9 | -4.76 | -75.1 | -2.29 | -15.7 | -4.61 |
| Buy - Sell | 50.5 | 1.07 | 64.4 | 1.18 | 97.9 | 1.73 | -73.1 | -1.01 | 77.9 | 1.61 | | |

Table 14: Short term returns to signed trades

This table presents regression coefficients for the following regression specification: $r_{30} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $r_{30}$ is the return over the next 30 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 sign of the trade (buys are +1, sells are -1 and unsigned trades are 0) and returns over the past 30 minutes. The first and second columns presents results for transactions involving the crossing network brokerage desk, split by whether the transactions occur in a liquid or less liquid situation. Liquid situations are defined as periods falling in the lowest two quintiles of average ticker minute level quoted bid ask percentage spreads. Less liquid 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 to reduce the effect of outliers.

| | Desk | | Negotiated | | Algo | |
|---|---|---|---|---|---|---|
| | Liquid | Less liquid | Liquid | Less liquid | Liquid | Less liquid |
| Sign of trade | 0.003 | 0.042 | -0.007 | -0.080 | -0.001 | 0.097* |
| | (0.380) | (1.061) | (-0.102) | (-0.330) | (-0.056) | (2.436) |
| Returns t-30 | -0.047 | -0.116+ | -0.001 | -0.470** | 0.090* | -0.173** |
| | (-0.921) | (-1.962) | (-0.009) | (-3.500) | (2.681) | (-5.325) |
| R-squared | 0.003 | 0.019 | -0.003 | 0.236 | 0.010 | 0.051 |
| N | 54250 | 3285 | 786 | 113 | 88631 | 6813 |

Table 15: Order flow imbalances around CN transactions

This table presents average order flow imbalance on the quoting exchange around CN transactions. Each cell presents the average number of minutes with net buying order flow minus the number of minutes with net selling order flow over the stated horizon. For the purposes of this analysis, a minute with net buy signed trades is counted as +1, a minute with net unsigned trades or a minute with no volume count as 0 and a minute with net selling counts as -1. For example, on average over the next ten minutes for all buy signed trades on the CN, there will be 0.11 more minutes with net buy signed trades than minutes with net sell signed trades on the quoting exchange. Results are presented for all CN transactions, for the most and least liquid situations separately and for trades by members and the CN desk separately for the least liquid situations.

Panel A: All observations

| | One minute | | Three minute | | Five minute | | Ten minutes | |
|---|---|---|---|---|---|---|---|---|
| | Previous | Next | Previous | Next | Previous | Next | Previous | Next |
| Sell | -0.06 | -0.03 | -0.07 | -0.04 | -0.05 | -0.04 | 0.08 | -0.03 |
| Unsigned | 0.01 | -0.02 | -0.04 | -0.07 | -0.05 | -0.09 | -0.10 | -0.12 |
| Buy | 0.07 | 0.02 | 0.14 | 0.07 | 0.21 | 0.10 | 0.37 | 0.11 |
| All | -0.01 | -0.01 | -0.01 | -0.03 | 0.00 | -0.03 | 0.07 | -0.04 |

Panel B: Most Liquid Quintile

| | One minute | | Three minute | | Five minute | | Ten minutes | |
|---|---|---|---|---|---|---|---|---|
| | Previous | Next | Previous | Next | Previous | Next | Previous | Next |
| Sell | -0.08 | -0.04 | -0.14 | -0.10 | -0.16 | -0.14 | -0.12 | -0.30 |
| Unsigned | -0.01 | -0.04 | -0.11 | -0.11 | -0.17 | -0.14 | -0.34 | -0.26 |
| Buy | 0.07 | 0.02 | 0.12 | 0.00 | 0.13 | -0.07 | 0.13 | -0.37 |
| All | -0.02 | -0.03 | -0.08 | -0.08 | -0.10 | -0.12 | -0.15 | -0.30 |

Panel C: Least Liquid Quintile

| | One minute | | Three minute | | Five minute | | Ten minutes | |
|---|---|---|---|---|---|---|---|---|
| | Previous | Next | Previous | Next | Previous | Next | Previous | Next |
| Sell | -0.41 | -0.47 | -0.95 | -1.33 | -1.77 | -2.06 | -4.15 | -4.22 |
| Unsigned | -0.08 | 0.01 | -0.05 | 0.02 | -0.16 | 0.50 | -0.52 | 2.03 |
| Buy | 0.25 | 0.31 | 1.01 | 1.35 | 1.87 | 2.50 | 4.96 | 5.75 |
| All | -0.18 | -0.17 | -0.26 | -0.31 | -0.52 | -0.30 | -0.97 | -0.54 |

Panel D: Least Liquid Quintile - Member Trades

| | One minute | | Three minute | | Five minute | | Ten minutes | |
|---|---|---|---|---|---|---|---|---|
| | Previous | Next | Previous | Next | Previous | Next | Previous | Next |
| Sell | -0.54 | -0.53 | -1.49 | -1.48 | -2.70 | -2.27 | -5.76 | -4.45 |
| Unsigned | -0.14 | 0.01 | -0.24 | 0.26 | -0.15 | 0.89 | -0.55 | 2.33 |
| Buy | 0.42 | 0.50 | 1.51 | 1.63 | 2.69 | 2.87 | 6.29 | 6.62 |
| All | -0.25 | -0.19 | -0.50 | -0.34 | -0.85 | -0.31 | -1.38 | -0.51 |

Panel E: Least Liquid Quintile - Desk Trades

| | One minute | | Three minute | | Five minute | | Ten minutes | |
|---|---|---|---|---|---|---|---|---|
| | Previous | Next | Previous | Next | Previous | Next | Previous | Next |
| Sell | 0.19 | 0.07 | 1.94 | 0.44 | 2.57 | 0.74 | 1.98 | 1.69 |
| Unsigned | 0.09 | 0.02 | 0.96 | -1.05 | -0.27 | -1.40 | 0.00 | -2.57 |
| Buy | -0.16 | -0.32 | -0.77 | 0.11 | -1.15 | -0.10 | -0.89 | -2.80 |
| All | 0.06 | -0.08 | 0.88 | -0.12 | 1.04 | -0.24 | 1.02 | -1.09 |

Table 16: Information content on crossing networks on earnings days

This table presents regression coefficients for the following two regression specifications: (1) $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $\Delta s_{10}$ 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 and (2) $r_{30} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where $r_{30}$ is the return over the next 30 minutes and $g_i$ are the explanatory variables. These are the same specifications in Tables 8 (Panel A) and 14 (Panel B). The sample is all transactions on the crossing network for 100 representative stocks from June 2009 to Dec 2009 that occur on days with earnings releases. The explanatory variables are the same as in the previous Tables. In these tables, if a specification present in the original specification is missing, there are insufficient observations to accurately estimate the model. 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 to reduce the effect of outliers.

Panel A

| | Desk | | Negotiated | Algo | |
|---|---|---|---|---|---|
| | Liquid | Less liquid | Liquid | Liquid | Less liquid |
| Volume change (MM shares) | 0.094 | -261.172 | 1.824 | -0.005 | 5.322 |
| | (1.699) | (-1.295) | (1.008) | (-0.178) | (1.236) |
| Volatility change | 11.352 | 466.860 | -16.922 | -0.972 | 87.737 |
| | (0.578) | (2.226) | (-1.181) | (-0.150) | (1.515) |
| Market cap (BN) | 0.000 | 0.002 | 0.000 | -0.000 | -0.004+ |
| | (1.669) | (0.305) | (0.835) | (-0.586) | (-2.158) |
| Constant | -0.004 | 0.197 | -0.002 | 0.005 | 0.060 |
| | (-0.862) | (1.229) | (-0.167) | (0.396) | (0.834) |
| R-squared | 0.014 | 0.627 | -0.070 | 0.002 | 0.198 |
| N | 1064 | 15 | 26 | 2217 | 137 |

Panel B

| | Liquid desk | Liquid Neg | Liquid Algo | Less liquid Algo |
|---|---|---|---|---|
| Sign of trade | -0.060 | -0.666 | 0.038 | -0.041 |
| | (-1.126) | (-1.481) | (1.230) | (-0.916) |
| Return t-30 | 0.065 | 0.397 | 0.152 | 0.034 |
| | (0.275) | (0.933) | (1.321) | (0.073) |
| R-squared | 0.011 | 0.192 | 0.063 | -0.003 |
| N | 835 | 20 | 1604 | 136 |