Introduction	Data	Results	Conclusions

Informed Trading in Dark Pools

Sugata Ray

joint with Mahendrarajah Nimalendran

IGIDR EMF, Dec 2011

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Motivation			

What are dark pools/crossing networks

Relatively new equity market design

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As opposed to limit order books (and other quoting markets)

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What are dark pools/crossing networks

Relatively new equity market design

As opposed to limit order books (and other quoting markets)

 Networks look for matches and prices trades relative to quoting exchanges (generally at mid)

Why do we care? Fast growth, regulatory debate



The Economist - July 2011

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Asia and India			

"Extremely disturbed by the global trend towards dark pools.... [they have] no regulatory responsibility and ... the logical conclusion [to the trend] would be that the biggest chunk of the market would be opaque."

- Ravi Narain, MD, NSE, The Financial Times (2009)

"\$4.95 billion in shares were bought and sold from January to March [2011] on [Liquidnet's] dark pools in Australia, Hong Kong, Indonesia, Japan, Malaysia, New Zealand, Singapore and South Korea, compared with \$3.75bn a year earlier."

- Bloomberg, April 2011 (Implies 32% YoY growth)

"One of the biggest markets we want to be in in Asia is India [but] there is no mechanism in India for off-market crossing."

- Lee Porter, Liquidnet Asia, Bloomberg, April 2011

"The absence of over-the-counter trading platforms for stocks in India prohibits dark pools from operating in the country."

- Sandeep Parekh, founder of Finsec Law Advisers, Bloomberg, April 2011

Introduction	Data	Results	Conclusions

Faced with a limit order book that looks like this for LinkedIn:

		Bid					Ask		e
MM Name	Price	Size	Cum Size	Avg Price	MM Name	Price	Size	Cum Size	Avg Price
ARCA	73.57			73.570	ISLAND	73.65			73.650
BATS	73.53			73.535	DRCTED	73.67			73.660
NYSE	73.53			73.534	PSX	73.68			73.667
NSX	73.53	11	20	73.532	EDGEA	73.68			73.670
BYX	73.52		24	73.530	BYX	73.68			73.672
PSX	73.46		25	73.527	NYSE	73.68			73.673
ISLAND	73.46		26	73.525	ARCA	73.72			73.680
CBSX	73.45			73.502	BATS	73.74			73.693
EDGEA	73.45		38	73.501	NSX	73.79			73.703
DRCTED	73.40	1	39	73.498	CBSX	74.10	4	14	73.816

■ \$500K market order on limit order book - not good

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- Use both QE and CN?
- What if trader has some private information about LNKD?

Introduction	Data	Results	Conclusions

This study: Informed trading in dark pools and the effects

- Is there informed trading in dark pools? How do we measure it? Where is it concentrated?
 - Almost all theoretical models suggest including CNs in strategy set helps maximize profits for informed traders
 - However, results critically dependent on parameters of model (shelf life of information, liquidity in CNs, depth of limit order book, how correlated is the information)
 - Other analogous venues without much informed trading: Upstairs markets, regional exchanges.

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 - Other analogous venues without much informed trading: Upstairs markets, regional exchanges.
- How does this affect market quality for participants in quoting exchanges?
 - Predictions are more mixed
 - We examine profitability of CN trades as well as whether QEs factor in information that may be available to CN traders

Introduction	Data	Results	Conclusions
Academic literature	e and our contr	ibution	

Theory: Zhu (2011 WP), Ye (2009 WP), Buti et al (2010 WP), Hendershott and Mendelson (2000 JF)

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 - Counterparty detail: Where is the information

Introduction	Data	Results	Conclusions
Details of the	data and repre	sentativeness	

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- We selected a list of 100 tickers, spread evenly across market cap, bid ask spreads, primary exchange, SIC codes (with slightly higher weight on large caps) - received transaction data for these tickers from June 2009 to Dec 2009 on the CN

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- Tickers are representative, CN constitutes 8% of of CN market share over this period (in line with what it normally constitutes)

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- Tickers are representative, CN constitutes 8% of of CN market share over this period (in line with what it normally constitutes)
- CN space is quite fragmented (40-50 CNs, the biggest has 10-15% market share, a few have 5-10% market share)

Introduction	Data	Results	Conclusions

Transactions on the CN over the course of the day



Introduction	Data	Results	Conclusions
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Brokerage Desk Like any other agency, often times a crossing network will "work" large orders for some of the customers on their system.

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network will "work" large orders for some of the customers on their system.

Member negotiated Trades involving two large "natural" traders that are manually negotiated. 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.

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Member algo Trades between members or between a member and external liquidity supplied from another dark venue. 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.

Introduction	Data	Results	Conclusions

Summary Statistics: Counterparties

Volume (Total =355MM shares)				
	External	Member	Total	
Desk	11.7	0.6	12.3	
Member Algo	25.6	2.8	28.4	
Member Negotiated	2.4	56.9	59.3	
Total	39.6	60.4	100.0	
No of trades (Total = 490K)				
	External	Member	Total	
Desk	35.8	0.0	35.8	
Member Algo	63.4	0.1	63.5	
Member Negotiated	0.1	0.6	0.7	
Total	99.3	07	100.0	

Introduction	Data	Results	Conclusions

Summary Statistics: Signed trades

Volume (Total =	355MM sha	res)	
	Sell	Unsigned	Buy	Total
Desk	3.80	6.10	2.50	12.30
Member Algo	7.70	17.00	3.80	28.40
Member Negotiated	2.90	53.50	2.90	59.30
Total	14.30	76.50	9.10	100.00

No of trades (Total = 490 K)				
	Sell	Unsigned	Buy	Total
Desk	15.50	11.60	8.60	35.80
Member Algo	27.20	24.10	12.20	63.50
Member Negotiated	-	0.60	-	0.70
Total	42.70	36.30	20.90	100.00

Introduction	Data	Results	Conclusions

Summary Statistics: Pricing deviations from mid (DFM) of NBBO

DFM (dollars)	Fraction of transactions (%)
-0.02 or less	3.48
-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 or more	5.37

Introduction	Data	Results	Conclusions

A limit order book within a limit order book



Zhu (2009): "Some dark pools passively match buyers and sellers at prices derived from transparent exchange; many others are essentially invisible limit order books that execute orders by price and time priority."

Introduction	Data	Results	Conclusions
Empirical test	s for informed	trading	

 How do transactions on dark pools affect spreads (and other measures of quoting market liquidity)

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Empirical tests for	informed tradir	าg	

 How do transactions on dark pools affect spreads (and other measures of quoting market liquidity)

Are signed trades in dark pools profitable?

Introduction	Data	Results	Conclusions

Informed trading occurs on CN

Introduct	tion	Da	ta	Results	Conclusions

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- Presence of information (although not information itself) becomes known
- Maybe the informed trader is simultaneous trading on QE, maybe another trader with correlated information is trading on QE
- Effect: If there is informed trading in CNs, we would expect spreads to rise following CN transactions

Conclusions

Average change in percentage spreads following a CN transaction - 10 min before vs. 10 min after

Liquidity	Desk	Negotiated	Member	Total	Base
			Algo		(median)
Liquid	0.006	0.004(NS)	0.016	0.012	0.061
2nd quint.	-0.008	-0.020	0.005	0.001	0.151
3rd quint.	-0.027	-0.043	-0.005	-0.010	0.447
4th quint.	0.014	0.014(NS)	0.033	0.026	1.048
Illiquid	0.220	0.057(NS)	0.315	0.294	5.185
Total	0.001	-0.012	0.013	0.009	0.103

All significant to at least a 5% level except those marked (NS)

Introduction	Data	Results	Conclusions
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Change on ch	ange regression		

 $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δs_{10} is the change in the average quoted percentage spread from 10 min before transaction to 10 minutes after

	All	Desk	Member Neg.	Member Algo
α	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
Ν	225003	78388	1332	145268

Controls: Change in volume, change in volatility, market cap

Interpretation: On average, after any trade on a CN, the spread increases by 1.0bp. After a trade by a member using algorithms, the spread increases by 1.4bp.

Introduction	Data	Results	Conclusions
Change on cl	nange regression		

 $\Delta s_{10} = \alpha + \sum_i \beta_i g_{i,t} + \epsilon$ where Δs_{10} is the change in the average quoted percentage spread from 10 min before transaction to 10 minutes after

	Liq. desk	Illiq. desk	Liq. Neg	Illiq. Neg	Liq. Algo	Illiq. Algo
α	-0.001	0.048+	-0.008+	0.048	0.008+	0.133*
	(-0.451)	(1.889)	(-1.902)	(0.887)	(1.966)	(2.238)
R2	0.070	0.212	0.037	0.287	0.092	0.231
Ν	66203	4201	906	154	109072	9495
<u> </u>		· ·	1	· · · · · · · · · ·		

Controls: Change in volume, change in volatility, market cap

Interpretation: On average, after a trade by a member using algorithms for an illiquid stock, the spread increases by 13.3bps

Introduction	Data	Results	Conclusions
Do signed CN tr	ades make	money?	

■ Signing - mid +/- x pennies - indicates a motivated trader

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Do signed CN trades make money?

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- Relative limit market within a limit market?
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 - In the case of fundamental and technical information, either informed traders (or others aware of the information) also trade on QEs
 - In the case of order imbalance strategies, the QE order book is replenished

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Do signed CN trades make money?

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 - In the case of fundamental and technical information, either informed traders (or others aware of the information) also trade on QEs
 - In the case of order imbalance strategies, the QE order book is replenished
- Prices in the QE move and short term returns are realized (could also be the result of news release)

Introduction	Data	Results	Conclusions

Long buys and short sells - Returns over next hour I

	Ret(bp)	T-stat	Ν
Sell	-2.0	-4.05	73,204
Unsigned	-1.5	-3.17	67,292
Buy	11.9	10.11	35,684
Buy - Sell	13.9	10.89	

Signed trades make money - portfolio makes 13.9bps over the hour (955% per year if annualizable!)

Introduction	Data	Results	Conclusions

Long buys and short sells - Returns over next hour II

Sample	Buy - Sell	T-stat
All trades	13.9	10.89
Most Liquid	-5.5	-11.65
Least liquid	520.2	6.70
Least liquid - member algo	749.5	7.60
Least liquid - CN desk	-73.1	-1.01

Be wary of trading an illiquid ticker on a CN against a motivated trader. Trade loses 5.2% in the next hour! At least the CN brokerage desk is not involved in this.

Introduction	Data	Results	Conclusions
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Regression:	Returns on pr	icing mechanism	

 $r_{60} = \alpha + \sum_{i} \beta_{i} g_{i,t} + \epsilon$ where r_{60} is the return over the next 60 minutes and g_{i} are the explanatory variables

	Liq. desk	Illiq. desk	Liq. Neg	Illiq. Neg	Liq. Algo	Illiq. Algo
DFM (%)	6.652	-8.617	349.240	-49.801	-24.824	36.779*
	(0.230)	(-0.500)	(1.241)	(-0.747)	(-0.398)	(2.065)
R2	0.004	0.064	0.003	0.009	0.008	0.092
N	40170	2509	575	71	65572	5080

Control variables includes historical returns

Interpretation: when motivated members trade illiquid tickers they make 36 times the additional payment back in returns over 60 minutes!

Introduction	Data	Results	Conclusions
Noturo of informa	tion		
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Introduction	Data	Results	Conclusions
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- LT fundamental Value investing/other long term information we don't care about this
- ST fundamental Pre earnings release, for example affects spreads and returns
- ST technical Trading correlated stocks for example most high frequency trading strategies - affects returns, maybe spreads

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- LT fundamental Value investing/other long term information we don't care about this
- ST fundamental Pre earnings release, for example affects spreads and returns
- ST technical Trading correlated stocks for example most high frequency trading strategies - affects returns, maybe spreads
- CN pricing arbitrage Order imbalance leads to mid being off affects returns but not spreads

Introduction	Data	Results	Conclusions

Earnings days - Spread analysis

	Desk	Negotiated	Member	Total
	Desit	i i egotiateu	Algo	
Most Liquid	0.006	-0.002(NS)	-0.003	-0.001(NS)
2nd Liquid	-0.005(NS)	0.013(NS)	0.128	0.054
3rd Liquidi	0.019(NS)	-0.063	-0.016	-0.013
4th Liquid	0.209	-0.091(NS)	-0.024	-0.002(NS)
Least Liquid		No Obs	ervations	
Total	0.004(NS)	-0.021(NS)	0.012	0.010

Overall, spreads still increase. Spreads do not increase for illiquid tickers.

Earnings days - ST Return Analysis

Sample	Buy - Sell	T-stat
All trades	-42.5	-11.24
Most Liquid	12.6	3.57
Least liquid	-82.8	-9.33
Least liquid - member algo	-62.4	-8.73
Least liquid - CN desk	-123.9	-2.03

Signed trades underperform on earnings days - suggests motivated traders on CN do not have ST fundamental information.

Introduction		Data	Results	Conclusions
Conclu	usion			

 Definitely informed trading present. Evidence? Spreads increase after CN trades, signed trades make money.

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 Information concentrated in short term "technical" information, CN pricing arbitrage, mainly for illiquid tickers.

Introduction	Data	Results	Conclusions
Conclusion			
Definit	elv informed trading	present. Evidence? S	preads

- Definitely informed trading present. Evidence? Spreads increase after CN trades, signed trades make money.
 - Information concentrated in short term "technical" information, CN pricing arbitrage, mainly for illiquid tickers.
 - Information transmits quickly to quoting exchanges either same or different traders making similar trades on QE.

Int	roduction	Data	Results	Conclusions
С	onclusion			
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 - Information concentrated in short term "technical" information, CN pricing arbitrage, mainly for illiquid tickers.
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- Policy: Regulators if we don't care about "technical" information, this is fine, maybe improve post trade transparency. Traders - Be wary of trading against motivated traders on CNs

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 - The Economist: "require dark pools to publish their operating and membership criteria, so that investors can make a better [decision]"