Big data in Finance

Finance Research Group, IGIDR

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Introduction

- Who we are?
- A research group working in:
  - Securities markets
  - Corporate governance
  - Household finance
- We try to answer policy questions using data and quantitative methods.

Case study

Paper: The causal impact of algorithmic trading on market quality
Authors: Nidhi Aggarwal & Susan Thomas
URL:
ifrogs.org/releases/ThomasAggarwal2014_algorithmicTradingImpact.html

The question

- Since 2000, escalating use of technology in trading on equities markets.
- AT now dominates exchanges worldwide. Concerns about liquidity, ‘flash crashes’, etc.
- Regulators all over the world are contemplating interventions on AT.
- In search of finding a market failure that justifies regulatory intervention, numerous researchers have asked: What is the effect of AT on liquidity and volatility?

Data

- Periods:
  - Pre co-lo: Jan '09 to Dec '09 (260 days)
  - Post co-lo: Jul '12 to Aug '13 (291 days)
- Criterion for securities selection: Study securities with at least 50 average daily trades in 2009 and 2012-13.
  This yields a set of 552 securities.
- Frequency used: Tick by tick trades and orders data.
- Data size analysed: 3.8 Terabytes of .csv text files.

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3. Two issues that are worrisome:
   - Endogneity: If liquidity is a reason for ATs to choose to focus trading on a stock, and liquidity is an outcome to be measured, then which way does the causality flow?
   - Threats to validity: Was the change in market quality because of AT or other factors, such as macro-economics?

This paper

1. A *clean microstructure*: An exchange with 80% market share of all trading, one of the largest exchange in the world by transaction intensity.
2. Uses *an exogenous event*: Introduction of co-location services in Jan 2010, which directly affected AT.
3. *Data*: Every order explicitly tagged as "AT" or "non-AT" for every security at the exchange.

Consolidated trading

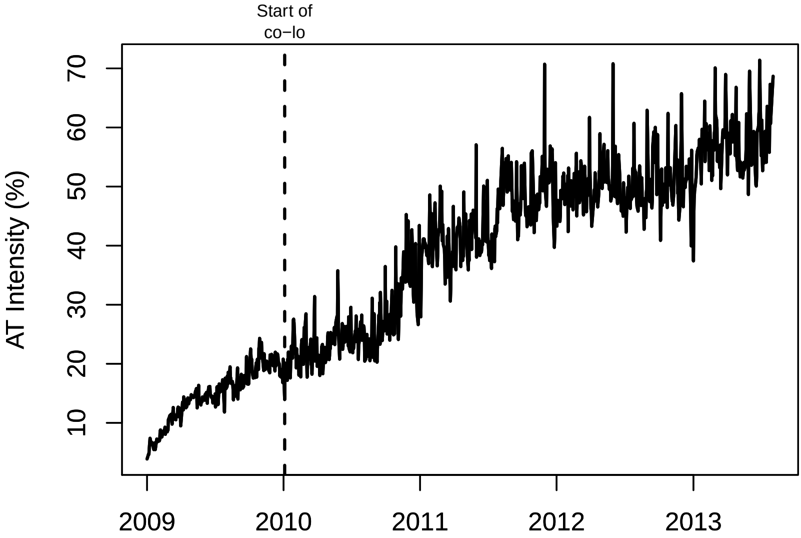
A big exchange by world standards

- In 2012 and 2013, NSE was the world's #1 exchange by number of trades on the equity market.
- The dollar value of these trades is small by world standards, but on this question, that is not important.

A natural experiment

- NSE launched co-location (co-lo) in January 2010.
- There was an S-shaped curve of adoption thereafter.
- This was an exogenous shock to AT intensity.

AT intensity between 2009-13

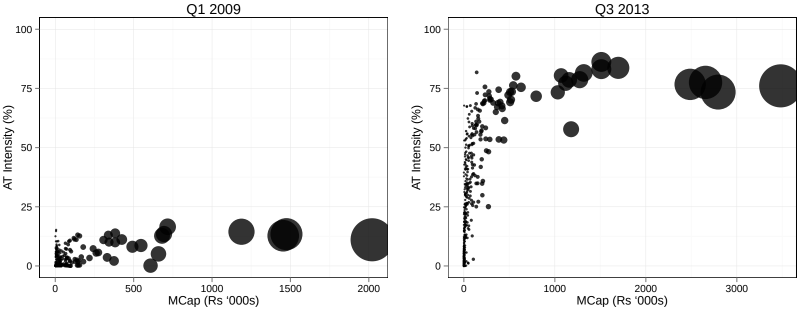


Issues in establishing causality

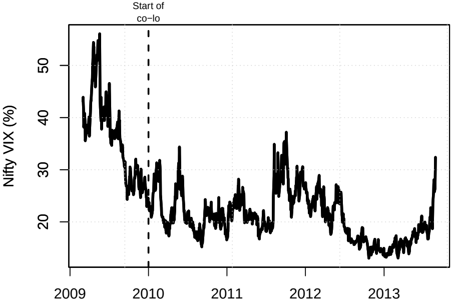
AT adoption at the firm level

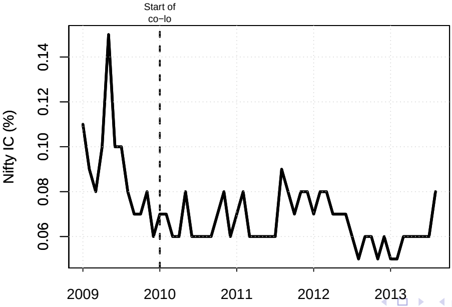
- Trading in some firms tend to become more AT while trading in some firms do not.
- Highly liquid firms tend to be more AT.
- There is the danger of selection bias here.

Variation in adoption of AT



Threats to validity: changes in macroeconomic conditions





I. Research design we use

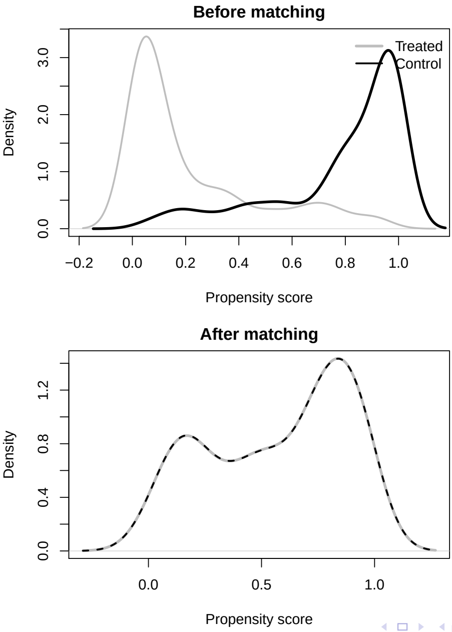
Matching at the security level

- We identify firms that got low AT adoption and firms that got high AT adoption.
- Use propensity score matching (PSM) to identify a matched sample.
- These are firms that are a lot like each other – but there was an almost experimental allocation where one group got the treatment of a surge in AT but the other group did not.

Obtaining set of matched firms

- After the launch of co-lo:
- Define
  - ‘Treated’: securities with Δ AT $> 70^{th}$ percentile value – 16.50% (276 firms)
  - ‘Control’: securities with Δ AT $< 30^{th}$ percentile value – 5.39% (276 firms)
  - Leave out firms in the middle.
- Propensity score matching:
  - Covariates: average daily values of market cap, price, floating security, turnover, number of trades (for the year 2009)

Density of the propensity score, before and after matching



Matching on macroeconomic conditions

- We capture changes in macroeconomic conditions by changes in the volatility of the market index (Nifty).
- We then match dates in the period before and after co-lo on volatility.
- This yields a set of dates in both periods which are alike in macroeconomic conditions.

Matching dates on macro-economic conditions

- Pick dates in the post co-lo period when market volatility matched the levels in the pre co-lo period (using Mahalnobis distance).
- This gives a set of 59 dates in each period that are alike.

Final sample characteristics

- Starting sample: Observations on 552 securities; Period of 260 days before co-lo and 291 days after co-lo.
- After matching on security level co-variates: 91 securities with high AT and 73 securities with low AT.
- After matching on macro-economic conditions: 59 days before co-lo and after co-lo.

II. Empirical setting

Market quality measures

- Liquidity
  1. Transactions costs
     1.1 QSPREAD (in %): (best ask - best sell)× 100 / mid-quote price.
     1.2 Impact cost (IC, %): execution cost of a market order at a size of Rs 25,000 relative to the mid-quote price.
  2. Depth
     2.1 TOP1DEPTH (in Rs.): Rupee depth available at the best bid and ask prices.
     2.2 TOP5DEPTH (in Rs.): Cumulated Rupee depth available at top five best bid and ask prices.
     2.3 DEPTH (# of shares): Average of the outstanding buy side and sell side number of shares.
     2.4 |OIB| (in %): Difference in buy and sell side depth as a percentage of the total depth, on average.

Market quality measures (contd..)

- Volatility
  1. Price risk, RVOL: Standard deviation of five-minutes returns.
  2. Price risk, RANGE: Difference in highest and lowest mid-quote price in a five-minutes interval.
  3. Liquidity risk, LRISK: Standard deviation of IC in five-minutes intervals.
- Efficiency
  1. VR: Ratio of 10-min variance of returns to 5-min returns
  2. KURTOSIS: Value of kurtosis in a five minute interval (absolute value).

What we find

Estimation using a Difference-in-Difference regression with matched securities and matched dates.

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1 \text{AT-DUMMY}_i + \beta_2 \text{CO-LO-DUMMY}_t + \\ &\quad \beta_3 (\text{AT-DUMMY}_i \times \text{CO-LO-DUMMY}_t) + \epsilon_{i,t}\end{aligned}$$

	β_3	Expected sign
QSPREAD	-0.35^{+}	$-$
IC	-0.80^{+}	$-$
|OIB|	-14.34^{+}	$-$
DEPTH	-0.08	$+$
TOP1DEPTH	0.09	$+$
TOP5DEPTH	0.25^{*}	$+$
|VR-1|	-0.03^{+}	$-$
KURTOSIS	$\mathbf{6.81}^{+}$	$-$
RVOL	-2.88^{+}	$-$
RANGE	-19.86^{+}	$-$
LRISK	-0.02^{+}	$-$

What we find, contd.

- Kurtosis is the incidence of extreme returns. Does higher kurtosis mean more flash crashes?
- We analyse how frequently:
  1. Traded prices move by 2%, 5% or 10%
  2. In a period of 5 minutes

  before co-lo and after co-lo.
- What we find:

in %

	Pre co-lo		Post co-lo	
	High-AT	Not	High-AT	Not
TWO-EXCESS	33.35	33.46	29.36	36.84
FIVE-EXCESS	5.21	5.65	5.30	7.85
TEN-EXCESS	1.01	0.91	1.42	1.29

Some more facts

Are ATs consumer or providers of liquidity?

- A well-accepted hypothesis is that ATs trade at the cost of non ATs. They are assumed to take away liquidity, and do not supply it.

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- A well-accepted hypothesis is that ATs trade at the cost of non ATs. They are assumed to take away liquidity, and do not supply it.
- We investigate this hypothesis. We define:
  - AT liquidity demand: % of trades that were *initiated* by ATs irrespective of who provided the liquidity.
  - We calculate out of total trades:
    - **AT2AT**:% of AT trades where ATs were liquidity suppliers.
    - **nAT2AT**:% of AT trades where non-AT supplied liquidity.
  - Separate and similar calculations for Non ATs.
- Done for the period between Jan 2013 to Dec 2013.

The facts

Overall cash market:

in %

	Mean	Median	SD	Min	Max
AT-DEMAND	37.45	**37.75**	3.86	11.22	48.28
AT-SUPPLY	39.92	**40.11**	5.17	8.76	53.24
AT2AT	18.60	**18.80**	3.47	1.42	29.24
AT2nAT	21.33	**21.34**	2.03	7.34	25.91
nAT2AT	18.85	**18.91**	1.19	9.80	21.75
nAT2nAT	41.23	**40.92**	5.41	29.60	81.44

Nifty stocks

in %

	Mean	Median	SD	Min	Max
AT-DEMAND	47.12	**47.30**	4.21	17.12	58.41
AT-SUPPLY	56.12	**56.36**	5.34	18.31	67.98
AT2AT	28.95	**29.13**	4.36	3.64	40.89
AT2nAT	27.17	**27.21**	2.08	14.67	32.86
nAT2AT	18.17	**18.22**	1.38	13.48	22.56
nAT2nAT	25.71	**25.27**	4.92	15.96	68.20

Case study: Conclusion

- The world has shifted from manual to computer-supported trading in an extremely short time.
- A major new phenomenon that requires analysis.
- All the regulators of the world are interested.
- Rapidly growing literature.
- Four identified flaws: (a) Fragmented microstructure (b) No clear identification in data infrastructure (c) Lack of exogenous change in AT and (d) Problems of causal identification.
- Our research design addresses these four problems.
- Main result: AT is good for market quality, but a) no significant impact on the depth though, b) no evidence in support of increase in flash crashes.

Thank you

anand.chirag@gmail.com
http://www.ifrogs.org/