Market quality in the time of algorithmic trading: Separating fact from fiction

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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?

Existing literature and what it says

Paper	AT/HFT identification
PROXY MEASURES	
Hendershott et al. (2011)	Rate of electronic message traffic
Frino et al. (2013)	Message traffic, Order-to-trade ratio
Hasbrouck and Saar (2013)	Strategic Runs
DIRECT MEASUREMENT	
Brogaard (2012)	NASDAQ HFT dataset
Brogaard et al. (2013)	"
Carrion (2013)	"
Hendershott and Riordan (2013)	AT flag
Chaboud et al. (2013)	AT flag
Jovanovic and Menkveld (2012)	Single HFT firm analysis
Menkveld (2012)	"

Findings: AT generally lowers transactions costs. AT may or may not improve depth. AT may or may not lower volatility.

Four difficulties of the existing literature

1. A lot of the literature uses data from U.S. markets, which have highly fragmented liquidity.
   If AT adoption was taking place in different ways in different places, it becomes difficult to pin-point the starting point to measure the impact on the overall market.

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2. Datasets often do not offer clear identification of AT. Without this, the measurement of AT activity is relatively weak.

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   If AT adoption was taking place in different ways in different places, it becomes difficult to pin-point the starting point to measure the impact on the overall market.
2. Datasets often do not offer clear identification of AT. Without this, the measurement of AT activity is relatively weak.
3. Some papers do use an exogenous change to carry out a before- and after- comparison. But this is not sufficient to establish causality.
4. 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?

Advantages in 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 was followed by an S-curve of adoption.
3. *Data recorded well*: Every order explicitly tagged as "AT" or "non-AT" for every security at the exchange.

With this context, the research design is better able to control for the threats to validity arising from macro-economic factors or endogeniety related to which securities are selected by AT.

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.

Consolidation of liquidity

The Indian equity market features exactly two trading venues:

	NSE	BSE	OTC market	Total
Equity spot	75	25	0	100
Equity derivatives	90	10	0	100

This is a clean setting compared with the fragmentation of equities trading elsewhere in the world.

Robust measurement of AT activity

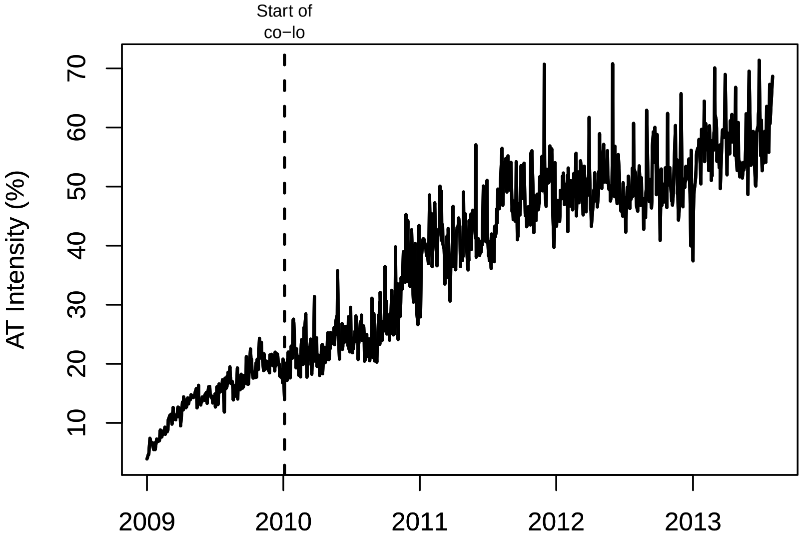
Measurement of AT activity

- Several well-cited papers in this field use proxies for AT activity.
  - Example 1: Hendershott et al (2011) uses electronic message traffic as a proxy for AT activity.
  - Example 2: Hasbrouck and Saar (2013) calculate "strategic runs" using order intensity for a security to capture HFT activity.
- NSE produces datasets where every order is tagged as AT or not, and the buyer and seller at every trade is tagged as AT or not.

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.
- This idea has also been used by Hendershott et al. (2011), Boehmer et al. (2012), Frino et al. (2013), Brogaard et al. (2013) etc.

AT intensity between 2009-13

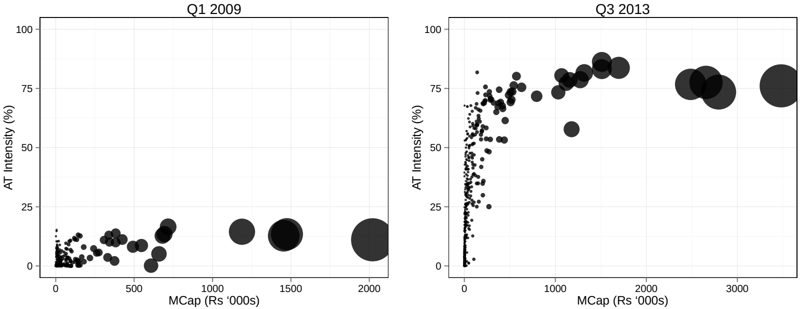


Issues in establishing causality

AT adoption at the firm level

- Trading in some firms tends to become more AT while trading in some firms does not.
- Highly liquid firms tends to be more AT, and we are trying to understand the impact of AT upon liquidity.
- There is the danger of selection bias here.

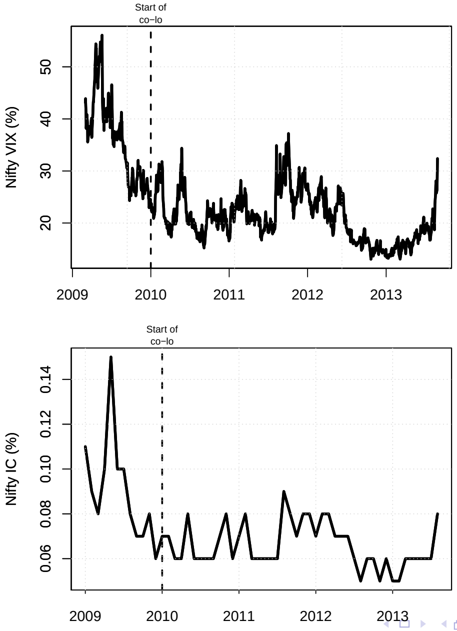
Cross-sectional variation in adoption of AT



Threats to validity: macroeconomic conditions

- Several papers compare market quality on certain high-AT dates vs. market quality on certain low-AT dates.
- In general, macroeconomic conditions may vary across these.
- E.g. during the global crisis, market quality was poor.
- We need to control for changes in macroeconomic conditions.

Changes in macroeconomic conditions



I. Research design we use

Causal identification by matching

- The exogenous shock to AT owing to the launch of co-lo is the basic identification opportunity.
- Matching dates by macroeconomic conditions + matching firms by propensity of AT adoption.
- This allows us to go beyond correlations, or before-after studies, and go closer to identifying the causal impact of AT upon market quality.

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.

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.

II. Empirical setting

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.

Market quality measures

- Liquidity
  1. Transactions costs
     1.1 QSPREAD (in %): (best ask - best sell)$\times$ 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.

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

	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	**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 %

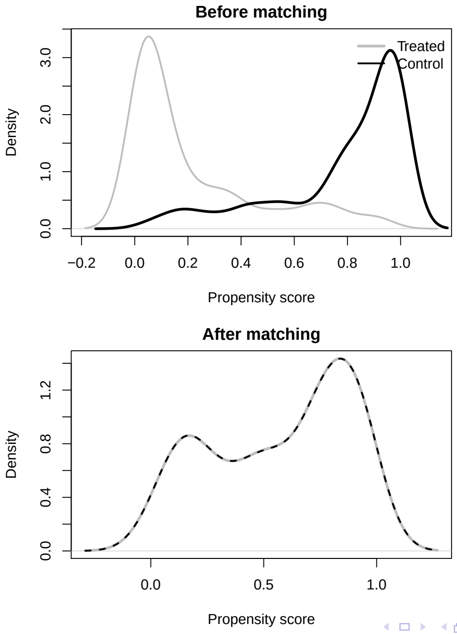
	Pre co-lo		Post co-lo	
	High-AT	Not	High-AT	Not
TWO-EXCESS	33.35	33.46	29.36	36.84
FIVE-EXCESS	5.21	5.65	5.30	7.85
TEN-EXCESS	1.01	0.91	1.42	1.29

III. The research setting

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)
  - Estimate logit model
  - Match on estimated propensity score with replacement, and very tight caliper of 0.01 (91 treated, 73 control)

Density of the propensity score, before and after matching



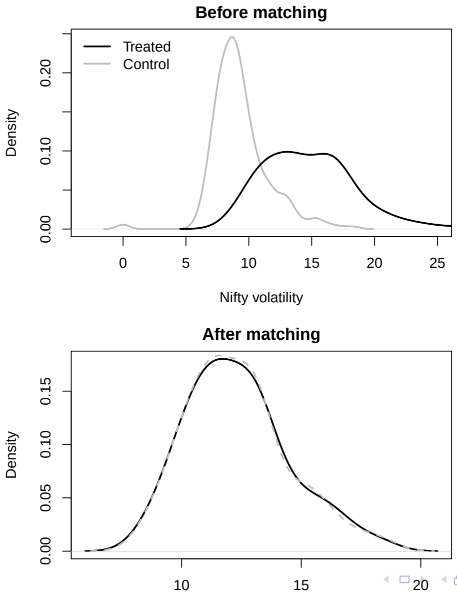
Balance statistics

Covariate	Before matching			After matching		
	t-stat	p-value		t-stat	p-value	
		t	KS		t	KS
MCap	22.13	0.00	0.00	-1	0.32	0.81
Price	16.84	0.00	0.00	0.25	0.80	0.22
Turnover	16.28	0.00	0.00	-1.58	0.12	0.12
# of trades	13.13	0.00	0.00	-1.42	0.16	0.06
Floating stock	-1.32	0.19	0.18	-0.09	0.93	0.60

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.

Macro-match evidence: Density of Nifty volatility, before and after matching



Match balance statistics

	Before Matching	After Matching
Mean (Treatment)	14.92	12.35
Mean (Control)	9.33	12.34
T-test p-value	0.00	0.41
KS p-value	0.00	1

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.

IV. Results

DID regression on matched securities, matched dates

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

Mkt-Quality	$\hat{\beta}_3$	Std. Error	t value	$Pr(>\|t\|)$	R^2	# of Obs.
QSPREAD	-0.35	0.05	-6.62	0.00	0.13	1,097,402
IC	-0.80	0.10	-8.03	0.00	0.18	10,94,922
$\|$OIB$\|$	-14.34	3.93	-3.65	0.00	0.07	1,097,402
DEPTH	-0.08	0.16	-0.52	0.60	0.02	1,097,402
TOP1DEPTH	0.09	0.17	0.56	0.58	0.09	1,097,402
TOP5DEPTH	0.25	0.15	1.66	0.10	0.09	1,095,752
$\|$VR-1$\|$	-0.03	0.01	-3.13	0.00	0.01	18,067
KURTOSIS	6.81	2.61	2.61	0.01	0.09	873,946
RVOL	-2.88	0.72	-4.00	0.00	0.05	1,094,673
RANGE	-19.86	7.06	-2.81	0.00	0.00	1,097,402
LRISK	-0.02	0.00	-5.31	0.00	0.02	1,094,686

Capturing extreme price movements

- Effect of AT on kurtosis value positive.
- Does it imply that AT increases the incidence of extreme price movements?
- Kurtosis, an ad-hoc measure to capture fat tails.
- We use another measure to capture extreme price movements:

  1. Compare the previous day's closing price and compute the percentage number of times in which the price movement within a five minute interval was beyond a certain threshold.
  2. We use three thresholds: 2%, 5% and 10%.
  3. Repeat the regression analysis using these measures.

Excess price movements: results

Summary statistics:

in %

	Pre co-lo		Post co-lo	
	Treated	Control	Treated	Control
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

DID regression:

Mkt-Quality	$\hat{\beta}_3$	Std. Error	t value	$\Pr(>\lvert t\rvert)$	F-stat p value	# of Obs.
TWO-EXCESS	-5.92	2.57	-2.30	0.02	0.00	870,106
FIVE-EXCESS	-1.53	1.39	-1.09	0.27	0.00	870,106
TEN-EXCESS	0.17	1.15	0.15	0.88	0.00	870,106

No evidence of more frequent extreme price movements due to AT.

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.

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.
- 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

Further work

1. AT behavior around extreme events (periods of fat-finger trades/flash crash)
    - Do they exhaust market liquidity around such periods? Or do they help by providing more liquidity?
    - Do they exacerbate volatility?
2. How do ATs behave around information related periods?
3. Do ATs get a better deal (in terms of trading costs) than the non ATs? Are non ATs adversely selected?
4. Do ATs aid price discovery?

Conclusions

- 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

Comments / Questions?

http://www.ifrogs.org/