The causal impact of algorithmic trading on market quality

Nidhi Aggarwal*, Susan Thomas**
*Indian Institute of Management, Udaipur, India
**Indira Gandhi Institute of Development Research, Mumbai, India

Introduction

The causal impact of algorithmic trading (AT) is difficult to establish due to endogeneity bias. Common factors such as macroeconomic events are likely to affect both AT and market quality. In addition, market quality and AT are jointly endogenous. For instance, AT might affect the liquidity of a stock, but it is also be affected by this liquidity. Thus, correlations between market quality variables should not be interpreted in terms of causality (Biais and Foucault, 2014).

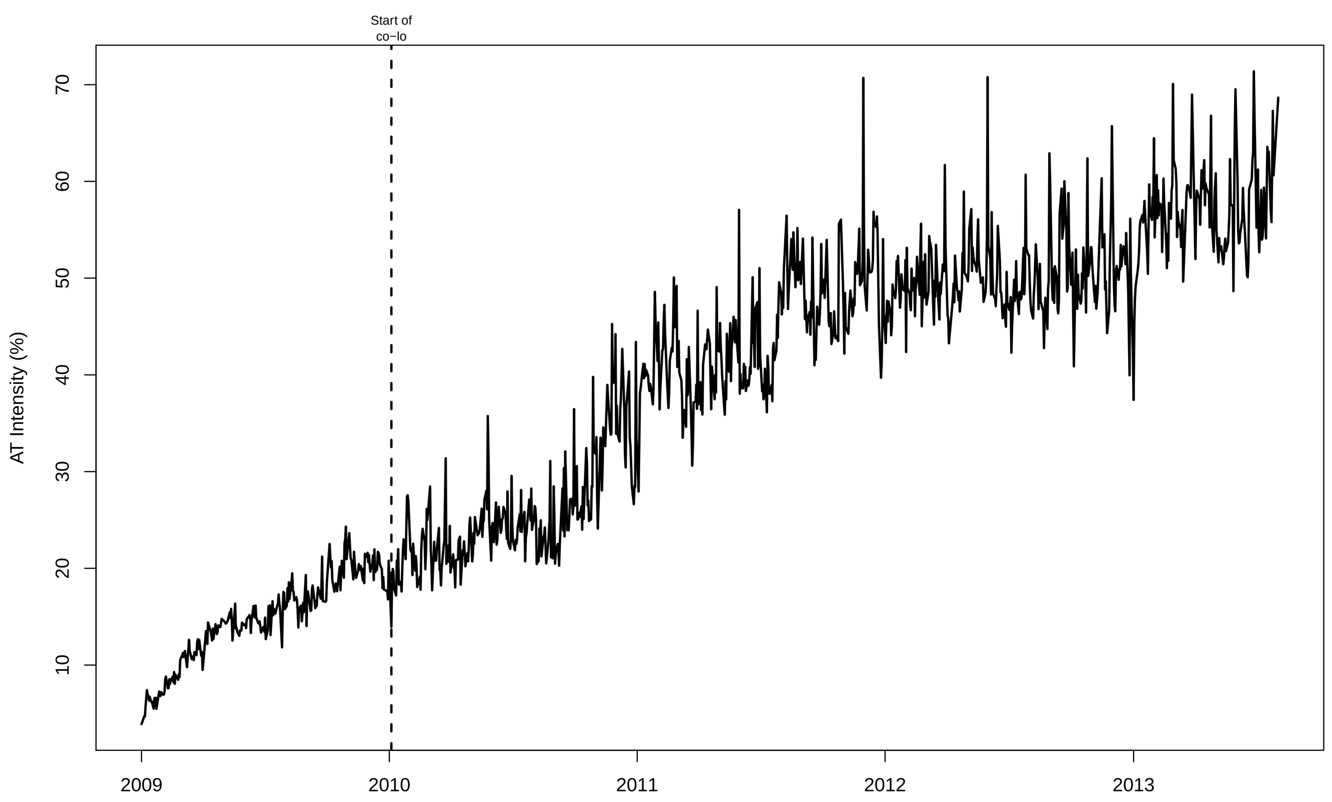
The second issue relates to the focus of the current literature on the US equity markets. Trading in the US markets is heavily fragmented, and a study of a single market in the US may not give the correct inference on how AT affects market quality, since the effect needs to be seen on the overall market.

This paper addresses the above issues in the following manner:

1. **Clean market microstructre**: The paper focusses on an exchange which has 80% market share in equity trading. This solves the issue of fragmented trading.
2. **An exogenous event**: The paper exploits an exogenous event of introduction of co-location after which AT increased.
3. **Data recorded well**: The paper uses a dataset where every single order is explicity tagged as 'AT' or 'non AT' for every security at the exchange.

Within this framework, the paper uses a research design which can better control for threats to validity that arise from macro-economic factors and endogeneity issues related to which securities are picked by AT.

The rise of algorithmic trading on the National Stock Exchange, India



Data

Using proprietary tick-level dataset of all orders and trades on the equity spot market from NSE, the paper analyses two periods:

1. Pre co-lo: Jan '09 to Dec '09 (260 days)
2. Post co-lo: Jul '12 to Aug '13 (291 days)

The dataset contains additional flag on whether the order or the trade was by an AT or non AT. A criterion of minimum number of average daily trades of 50 in 2009 and 2013 is imposed for securities selection. This yields us a set of 552 securities.

Issues in establishing causality

1. AT adoption at firm level
   i. Trading in some firms tends to become more AT while trading in others does not.
   ii. Highly liquid firms tend to be more AT, and there is a danger of selection bias if one only analyses top liquid securities.
2. Macroeconomic conditions
   i. Several papers compare market quality on high AT period and low AT period.
   ii. In general, macroeconomic conditions may vary across these two periods. E.g: global financial crisis.
   iii. We need to control for changes in macroeconomic conditions.

Research design we use

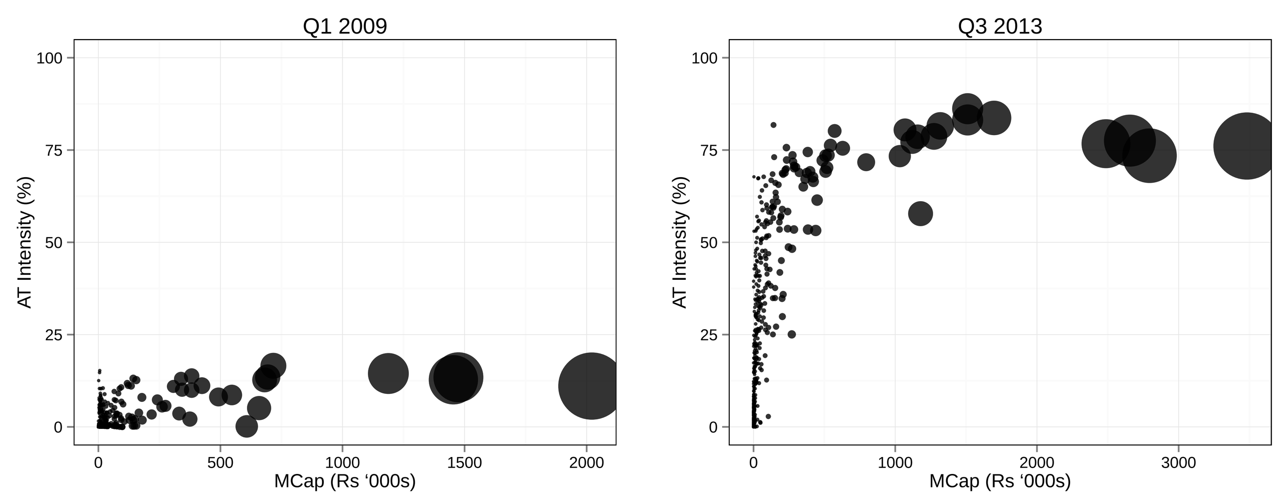
1. Matching at security level:
   i. We identify firms that got low AT adoption and firms that got high AT adoption.
   ii. Use propensity score matching to identify matched sample.
   iii. These are the firms that are lot like each other, but was an almost experimental allocation where one group got treatment of a surge in AT but the other group did not.
2. Matching on macroeconomic conditions:
   i. Pick dates in the post co-lo period when market volatility matched the levels in the pre co-lo period.
   ii. Use Mahalanobis distance to identify matched dates.

This allows us to go beyond correlations, or before-after studies, and go closer to identifying the causal impact of AT upon market quality.

Final sample: 91 treated, 73 control securities on 59 dates in the pre and post co-lo period.

Cross-sectional variation in adoption of AT

AT-pre **AT-post**



Results: *DID regression on matched securities, matched dates*

We estimate the following DiD regression:

$$\text{MKT-QUALITY}_{i,t} = \alpha + \beta_1 \text{AT-DUMMY}_i + \beta_2 \text{CO-LO-DUMMY}_t + \beta_3(\text{AT-DUMMY}_i \times \text{CO-LO-DUMMY}_t) + \beta_4(\text{NIFTY-VOL}_t) + \beta_5(\text{INTRADAY-DUMMY}_t) + \beta_6 \text{LTP}_{i,t} + \epsilon_{i,t}$$

Impact of algorithmic trading on market quality

Mkt-Quality	$\hat{\beta}_3$	Std. Error	t value	$\Pr(>\lvert t\rvert)$	R^2	# of Obs.
QSPREAD	**-0.35**	0.05	-6.82	0.00	0.14	1,094,827
IC	**-0.79**	0.10	-7.95	0.00	0.19	1,092,347
|OIB|	**-13.87**	3.98	-3.49	0.00	0.08	1,094,827
DEPTH	**0.33**	0.15	2.22	0.03	0.20	1,094,827
TOP1DEPTH	0.16	0.17	0.95	0.34	0.09	1,094,827
TOP5DEPTH	**0.33**	0.15	2.19	0.03	0.10	1,093,177
|VR-1|	**-0.03**	0.01	-3.13	0.00	0.01	18,067
KURTOSIS	2.76	2.48	1.12	0.26	0.14	873,946
RVOL	**-2.65**	0.71	-3.76	0.00	0.05	1,094,673
RANGE	**-16.90**	6.84	-2.47	0.01	0.00	1,094,827
LRISK	**-0.02**	0.00	-4.75	0.00	0.04	1,092,111

Impact on extreme price movements

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

Robustness tests

Test for threats to validity in case of overlooked factors, logical flaws in matching.

We address these concerns by simulating a placebo and by testing for sensitivity to match design.

Placebo test results: % of times the null is rejected

Mkt-Quality	Number of rejections of $\hat{\beta}_3 = 0$ (in %)
QSPREAD	1.7
IC	3.2
|OIB|	4.4
DEPTH	5.3
TOP1DEPTH	4.2
TOP5DEPTH	4.0
|VR-1|	3.7
KURTOSIS	3.6
RVOL	0.3
RANGE	4.6
LRISK	3.5

The null is rejected less than 5% of the times. Indicates that there is no impact on market quality in the absence of changes in AT.

DID $\hat{\beta}_3$ estimates with different set of matching covariates

Mkt-Quality	**Dropped covariate**				
	Floating stock	Market cap	# of trades	Price	Turnover
QSPREAD	-0.35^{+}	-0.59^{+}	-0.36^{+}	-0.30^{+}	-0.36^{+}
IC	-0.78^{+}	-1.12^{+}	-0.89^{+}	-0.73^{+}	-0.81^{+}
|OIB|	-16.10^{+}	-9.99^{+}	-17.87^{+}	-17.69^{+}	-15.11^{+}
DEPTH	0.31^{**}	0.25^{*}	0.16	0.10	0.33^{**}
TOP1DEPTH	0.05	0.01	0.13	-0.07	0.06
TOP5DEPTH	0.24	0.21	0.31^{**}	0.08	0.27^{*}
|VR-1|	-0.03^{+}	-0.03	-0.01	-0.03	-0.03
KURTOSIS	6.26^{+}	5.02^{**}	7.66^{+}	8.90^{+}	6.58^{+}
RVOL	-2.52^{+}	-5.57^{**}	-2.46^{+}	-2.19^{+}	-2.68^{+}
RANGE	-18.19^{+}	-24.00^{+}	-26.62^{+}	-15.03^{**}	-22.36^{+}
LRISK	-0.02^{+}	-0.02^{+}	-0.02^{+}	-0.01^{+}	-0.02^{+}

The results hold for all market quality variables except DEPTH, TOP5DEPTH which are sensitive to the match design.

Conclusion

The results suggests that

- Overall good for market quality in terms of higher liquidity and better price efficiency.
- No evidence in support of increase in flash crashes.
- Contrary to the existing literature, the evidence indicates that AT is beneficial for small stocks.

References

1. Hendershott T., Jones C. and Menkveld A. (2011) "Does algorithmic trading improve liqudity", The Journal of Finance
2. Biais B. and Foucault T. (2014), "HFT and Market Quality", Bankers and Market Quality