Algorithmic trading and the NSE equity markets: Has the market changed for the better?

Nidhi Aggarwal* Susan Thomas
Indira Gandhi Institute of Development Research

10 December 2014

*The authors are with the Finance Research Group, IGIDR. We are grateful to the National Stock Exchange of India, Ltd. for research grant and data support. We thank Ajay Shah for inputs into the research design and Chirag Anand for technological inputs.

Contents

1 Introduction

A recent target for public confusion and regulatory concern in financial markets has been the rapidity with which public markets for securities transaction can be accessed through the use of algorithmic trading through computers. There is confusion about how such a rapid access to the market can improve the quality of markets, and there are concerns that such access can instead lead to disruptions in the smooth performance of markets.

Most of these concerns have been difficult to prove or disprove. The academic literature has been consistent on the question of the impact of higher access through the use of algorithms running on fast computers: that the average quality of liquidity in markets have improved as a consequence. But these studies admit to the problem of *endogeneity*: typically, algorithm based trading is deployed on securities where there is already sufficient liquidity. The academic literature is yet to convincingly demonstrate that the improvements in liquidity after the start of algorithm based trading can be solely or largely due to this new mechanism of market access, and that it is a sufficiently general finding that can scale across all market microstructures and for all classes of investors.

After more than a decade of these systems being in place, regulatory concerns appear to have become better defined, with a focus on two main issues. One concern is about the higher probability of price disruptions over a very short period of time during the trading day. Another concern is about one set of market participants gaining an unfair advantage in earning profits at the expense of other participants by using algorithms to access markets first. The test of the first set of concerns is vulnerable to the same type of problems of endogeneity that applies to empirical results about the improvement in general market liquidity. The second set of concerns requires access to data with identities of counterparties in order to establish whether profits are being made consistently by one set of traders or the other. This is considered sensitive data which exchanges are typically unwilling to make public.

There are similar concerns in the Indian exchange traded markets (mostly trading equities), although they have been less excessive compared to the debates in more complex markets. This is largely because there is a higher degree of transparency in the Indian equities markets than in the multi-market microstructure ecosystem of the U.S. There securities trading takes place simultaneously in the large exchanges as well as in the smaller networks such as the ECNs and dark pools, and it is difficult to identify market failure or attribute the failure to algorithmic trading or high speed access as the source of the failure.

In addition to the higher transparency and lower complexity, there is also rich data available to analyse the effect of algorithmic trading in India, with both orders and trades from the largest equity market by volumes are tagged as originating from an algorithm or not. Since this is available for all traded securities, and the market is not fragmented beyond two large equity exchanges, there is a higher possibility of identifying the effect of algorithmic trading.

In this setting, we answer four questions:

1) What extent of the Indian equity market today is algorithmic trading (AT)?

2) What is the impact on the market quality for a stock where there is a higher presence of AT compared to that of a stock with lower AT? Does high level of AT contribute to greater incidence of extreme price movements leading to high price instability?

3) Are algorithmic traders at an advantage to non algorithmic traders? What is their role in providing liquidity?

4) Do AT provide liquidity opportunistically – does their participation change adversely during periods of market stress?

How much of the market can now be attributed to AT? Our analysis for the period between 2009-13 on the data from the National Stock Exchange suggests that while there has been a significant growth of AT in the Indian equity markets, it is not the sole form of trading, even more than five years after the regulator permitted its use. On average, 65 percent of the trades are generated by order placed by computer algorithms[1], with the remaining coming from trades by non algorithmic trades on both sides of the transaction.

What has been the effect of higher AT on the quality of the market, in terms of price efficiency, liquidity and volatility? Both the data and the public perception is that there has been a surge of AT in the securities markets globally. What is not so obviously presented from the data is that there is a wide variation in AT adoption across different stocks. Some stocks have a high degree of AT in who generates trades in those stocks, while others have a low degree of AT participation. In answering the question of how AT effects market quality, we cannot undertake an analysis about overall market behaviour before there was AT and after. Instead, we look for pairs of stocks which were similar in market capitalisation, floating stock and trading volumes, with similar AT, at the start of the period of AT adoption. We find that if there was greater AT adoption on one of the pair of stocks, then that stock also had higher liquidity and lower volatility than the stock which had lower AT adoption. This suggests that higher AT helps improve quality of market trading for stocks where there is higher AT intensity.

The data allows us to analyse which type of order initiates any trade. We analyse how many of the trades in the market are initiated by AT, and how many are initiated by non AT orders. We can also analyse whether the counterparty to this trade is another AT order, or whether it is a non AT order. We find that in the spot market, the trade origination is balanced almost equally between AT as originators and non AT as originators. Among these orders, around 45 percent are non AT orders matched against non AT orders, while around 15 percent are AT orders matched with AT orders. This suggests that, on average, AT does not take all the liquidity from the market, and instead, plays the role of providing liquidity as much as the non AT do.

We also analyse whether this behaviour of providing liquidity changes during times of extreme market stress. In order to do this, we undertake a case study of an event that sharply disrupted the prices in the market: the Emkay crash of October 5, 2012. We examine the behaviour of AT order placement around the period of the crash and compare it with their behavior on normal days. We find that When the market opened after the five minute closure caused due to more than 10% percent drop in Nifty, there

[1]This includes AT on both sides of the trade, or an AT on only one side of the trade.

was no significant change in the order posting behavior of algorithmic traders.

In summary, we have not yet closed the story about how AT effects market quality, particularly from the viewpoint of the concerns of regulators and the public at large. There are also some unexplained questions from a research perspective For instance, why do traders who use algorithms prefer some stocks over others, even though they share similar characteristics such as market capitalisation, price, traded volumes and volatility? Could there have been other market microstructure changes that caused the liquidity and the volatility to change, and simultaneously caused the changes in market quality? This paper does not answer all these questions.

What this paper does answer is a limited set of questions that are emblematic of the fears of the policy maker and the public. And the answer is that AT appears to leads a security to have more robust and improved market quality.

2 What is algorithmic and high frequency trading?

Algorithmic trading (AT) relies on the use of computer algorithms to make decisions about order submissions and cancellations. It facilitates rapid decision making and reduces reaction time to news and information, which puts those who use AT at an advantage over the traditional non-algorithmic trader (non AT). It involves a variety of algorithms ranging from strategies that exploit simple arbitrage opportunities, to more sophisticated ones such as optimal execution of orders. High frequency trading is essentially a subset of algorithmic trading, specifically by proprietary firms. The distinguishing feature of high frequency proprietary algorithms is their reliance on low-latency environment to react to market events.[2] This requires investment in co-location facilities and advanced computer technology.

The Securities and Exchange Commission of the U.S. [3] defines high-frequency traders as "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on daily basis." They characterize HFTs by: (1) the use of *extraordinarily high-speed* and *sophisticated computer programs* for generating, routing, and executing orders; (2) use of *co-location* services and individual data feeds offered by exchanges and others to minimize network and other types of latencies; (3) *very short time-frames* for establishing and liquidating positions; (4) the submission of *numerous* orders that are canceled shortly after submission; and (5) ending the trading day in as close to a *flat* position as possible (that is, not carrying significant, unhedged positions overnight) (SEC (2010)).

Technological advances in the last few years have fueled the growth of algorithmic and high frequency trading globally. Carrion (2013) estimates HFT participation of 68.3% of all dollar trading volume for a sample of 120 stocks which covers the period of 2008 and 2009. On 30 DAX stocks, Hendershott and Riordan (2013) document that AT represents 52% of market order volume and 64% of non-marketable limit order volume.

[2]See Jones (2013) for a description of type of strategies undertaken by HFT.

[3]SEC

Hagstromer and Norden (2013) analyse 30 Swedish stocks traded on NASDAQ-OMX Stockholm Exchange and find that HFT constitutes 25-50% of the total trading activity on these stocks.

The rise in AT activity has however not gone well with the regulators and investors. There is a lot of concern on whether AT in general, and HFT in particular, is good or bad for the markets. The concerns include whether AT and HFT provide additional liquidity or take it away, do they cause market disruptions by exiting at their discretion, especially so during the stress periods. Concerns on AT/HFTs ability manipulate the markets are also abound. Kirilenko and Lo (2013) in their survey of literature on algorithmic trading, point out that while automated trading has benefited the intermediaries, the cost has come in terms of larger frequency of technological malfunctions, price volatility spikes, and failures and frauds of intermediaries. It is also claimed that the benefits have largely accrued disproportionately to a limited set of participants in the markets. This has raised concerns about regulators ability to protect investors interests.

In the next section, we discuss the literature which analyses algorithmic trading and high frequency trading from the viewpoint of the above mentioned issues.

3 Global analytical and policy thinking: Evidence so far

The policy debate on AT and HFT has focussed academic interest in this area. However, a lack of relevant data has restricted the scope of the analyses. Proponents argue that algorithmic and high frequency traders are the new market makers and perform an important function of liquidity provisioning. Critics, on the other hand, argue that fast traders make profits at the cost of retail and slow traders, and also cause high volatility in the markets.[4] Several recent papers examine the validity of the concerns. Some of the questions this literature deals with are:

1. What is the impact of algorithmic and high frequency trading on market quality? How has the growth in the level of AT/HFT impacted investor welfare?
2. What is their role in market making and liquidity provisioning and consumption?
3. Does algorithmic and high frequency trading increase the risk of market crashes?

The first of these is a key question in the policy debate: are there returns to higher levels of investment in algorithmic and high frequency trading by way of higher market quality?

Theoretical research on this issue include Jovanovic and Menkveld (2010), Biais *et al.* (2015), Hoffmann (2014), Cartea and Penalva (2012), Martinez and Rosu (2013). Jovanovic and Menkveld (2010) model the impact of high frequency traders on investor welfare in limit order markets. The ability of HFTs to update limit orders quickly based on new information can improve investor welfare by reducing adverse selection. However,

[4] *High-frequency trading under scrutiny*, Michael Mackenzie, Financial Times, July 28, 2009.

if no adverse selection problem existed before, and the new information gets only known to the HFTs initially, they show that HFTs can reduce welfare. Biais *et al.* (2015) also analyse high frequency traders, and show that fast traders can have a positive impact on social welfare by enhancing mutual gains from trade. At the same time can cause negative externalities to slow traders by imposing adverse selection cost. Cartea and Penalva (2012) add high frequency traders to Grossman and Miller (1988) model and analyse their interaction with the two other types of traders: liquidity traders and professional traders (market makers). They show that presence of HFTs make the liquidity traders worse off, by increasing the price impact of their trade as well as the volatility of the prices.

Hoffmann (2014) modifies Foucault (1999) by introducing fast traders into the limit order market. Conditional on the level of market efficiency, the study shows that HFTs can have a positive impact on market liquidity. Martinez and Rosu (2013) model HFTs as informed traders who observe a stream of signals and find that they do not destabilize the markets, but rather make markets more efficient by incorporating information into prices quickly. In all, the theoretical evidence is mixed and suggests that the net impact of high frequency traders on investor welfare depends on the initial market conditions, and HFT strategies.

Empirically, several studies analyse the impact of algorithmic and high frequency trading on market quality. Using proprietary dataset, Menkveld (2013), Carrion (2013), Brogaard (2010), Brogaard *et al.* (2014b), examine the role of high frequency traders in facilitating price discovery and price efficiency. They find that HFTs play a beneficial role in enabling price efficiency and provide liquidity around stressful times.

Zhang (2010) on the contrary, uses a proxy to observe HFT and finds that high frequency trading is negatively related to price formation and also increase volatility. Hasbrouck and Saar (2013) develop a new proxy based on strategic runs to assess the level of high frequency trading in the markets and its impact on market quality. The study finds that increased high frequency trading improves market quality measures in the form of narrower spreads, higher displayed depth and lowered short term volatility.

With an explicit focus on algorithmic trading activity, Hendershott *et al.* (2011) analyse the effect of AT on the New York Stock Exchange using automated quote dissemination as an exogenous event that positively affected the level of algorithmic trading activity in the market. They use electronic messages as a proxy for identifying algorithmic trading and find that AT lowers liquidity costs, and also enhance quote informativeness. This effect is strong for large market capitalization stocks.

While most of the above studies are on the US markets, a few studies have also looked at other exchanges. Riordan and Storkenmaier (2012) examine how drop in latency at the Deutsche Bourse impact the market quality. They find a positive impact on market quality (by way of drop in spreads and increases in price efficiency). Few studies such as Viljoen *et al.* (2014), Frino *et al.* (2013) also examine the impact of algorithmic trading on the futures market. They find a similar positive impact of algorithmic trading on liquidity and price efficiency. Lee (2013) examines the impact of high frequency traders on KOSPI 200 index futures market, but finds that HFTs have a detrimental effect on market quality. The study concludes that neither do the HFTs provide any additional liquidty, nor do they improve the price discovery process. Bohemer *et al.* (2012) find similar results for 39 exchanges. They however find that higher AT activity is related to higher volatility in the markets. In contrast, Chaboud *et al.* (2014) study the foreign exchange market and find no evident causal relationship between algorithmic trading and increased exchange rate volatility.[5]

Broadly, evidence from most of the empirical studies suggests that algorithmic or high frequency trading improves liquidity costs and price discovery function of the markets. There is a lack of clarity on how these traders affect the volatility in the markets. Kirilenko *et al.* (2017) investigate the behavior of high frequency traders around the U.S. flash crash of May 6, 2010, and find that though HFTs did not trigger the flash crash, their activities exacerbated market volatility on that day.[6] Golub *et al.* (2012) analyse the mini flash crashes on the US equity markets in the period between 2006-11 and find that these crashes were the result of regulatory framework and market fragmentation. A recent paper by Brogaard *et al.* (2014b) analyses the relation between high frequency trading and extreme price movements on the US markets. Contrary to the popular perception that HFTs exacerbate market instability, the paper finds that HFT activities stabilise the markets around price jumps.

Malinova *et al.* (2013) study the impact of a drop in the level of algorithmic trading due to the imposition of a fee by the regulator on the number of messages by algorithmic traders at the Toronto Stock Exchange. They find that, while trading costs increased for institutions, retail investors remained unaffected. They also find that the adverse selection costs increased for all investors after the level of algorithmic trading went down. Using data from the London Stock Exchange, Brogaard *et al.* (2014a) examine the impact of high frequency trading on the execution costs of institutional investors. They find that penetration of HFT in to the markets did not have any clear impact on the tradings costs of institutional investors.

Despite such evidence suggesting that algorithmic or high frequency trading does not harm the markets on an average, the concerns still remain. Some of these are due to the lack of perfect data used in the analysis, and other due to the methodology used in the studies that does not necessarily provide a causal relation (Biais and Foucault (2014), Aggarwal and Thomas (2014)). Episodes of market glitches[7] have further raised the concerns that higher levels of high frequency trading has made the markets more vulnerable. As a result, regulators worldwide are contemplating several policy actions that can be taken to curb this activity. These include imposition of minimum order exposure time SEC (2010), excessive orders fee, introduction of batch auctions Budish *et al.* (2014). Similar concerns exist in the context of the Indian equity markets with a

[5]Other studies also look at the liquidity provisioning function of algorithmic traders. Hendershott and Riordan (2013) find that algorithmic traders demand liquidity when it is cheap and supply liquidity when it is expensive. Carrion (2013) study the high frequency trading strategies and find that HFTs provide liquidity when it is scarce and consume when it is plentiful.

[6]Scholtus *et al.* (2014) examine the impact of high frequency trading on market quality around the US macroeconomic news releases. They find that periods around macroeconomic news releases are characterized by large (quoted) spreads, increased volatility, decreased depth, and increased algorithmic trading activity.

[7]For example, US flash crash of 2010, programming glitch at Knight Capital in August 2012.

range of proposed interventions.[8]

This paper seeks to provide some empirical evidence on the effect of algorithmic trading on the Indian equity markets using data from the National Stock Exchange. Specifically, we answer the following questions:

1) What extent of the Indian equity market today is algorithmic trading (AT)?
2) What is the impact on the market quality for a stock where there is a higher presence of AT compared to that of a stock with lower AT? Does high level of AT contribute to greater incidence of extreme price movements leading to high price instability? What is the impact on price efficiency, volatility and liquidity?
3) Are ATs at an advantage to non ATs? Do ATs tend to always consume liquidity provided by non ATs, but do not provide liquidity to non ATs?
4) Does the participation of ATs change during periods of market stress periods?

4 Data

The analysis uses a data-set of all orders and trades that occur on any stock listed on the National Stock Exchange during 2009-13. Both the orders and trades data are time-stamped to the millisecond level, with details on whether the order and trade was by an algorithmic trader or a non-algorithmic trader. This information helps us to clearly identify the level of algorithmic trading activity on a stock (and for the market as a whole). In addition, the data also have details on the type of trader category specifying whether the order and trade was by a custodian (institutional), proprietary firm or a non custodian non proprietary[9] trader. The study utilizes ALL stocks listed on the National Stock Exchange Ltd. as of August 2013. The number of such stocks was 1577.

5 What extent of the Indian equity market today is algorithmic trading (AT)?

Algorithmic trading on the Indian equity markets was permitted by the market regulator in April 2008.[10] However, high levels of latency prevented the market participants to invest in algorithms. As a result, the level of algorithmic trading on the Indian markets remained very low in 2008-09.[11] In January 2010, exchanges introduced co-location facilities, which allowed traders to place their servers near the exchange premises. Latency dropped from 10-30 ms to 2-6 ms. The period post the introduction of co-location facilities saw a substantial increase in algorithmic trading.

[8]Examples include imposition of system induced latency, use of two separate queues for co-located and non co-located orders (SEBI (2013)).

[9]This includes retail investors, hedge funds etc.

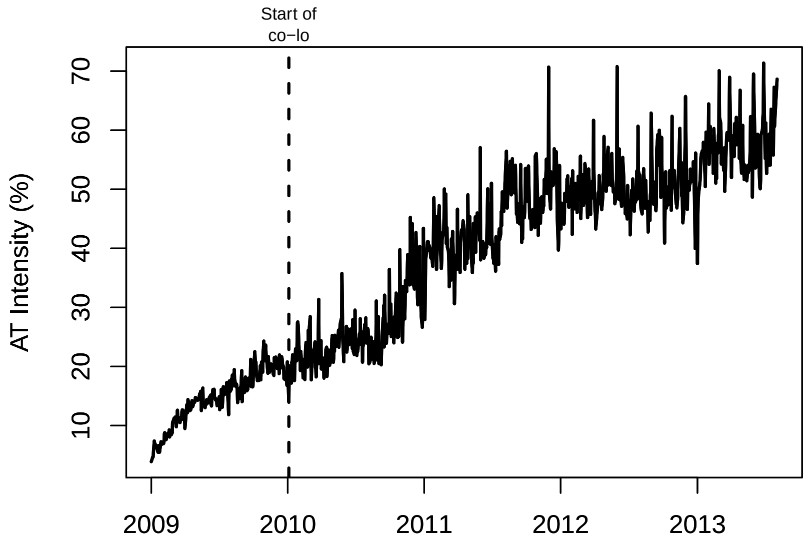
[10]Prior April 2008, algorithmic trading was restricted to arbitrage related strategies only.

[11]*Indian markets slowly warming up to algorithmic trading*, The Mint, July 14 2009.

Figure 1 shows the time-series evolution of algorithmic trading intensity on NSE's spot market between 2009 to 2013.[12]

Figure 1 AT intensity on NSE's spot market between 2009 and 2013

The graph shows AT intensity for the overall equity spot market at NSE between 2009 and 2013. AT intensity is measured as a fraction of total traded value of AT trades in a day vis-a-vis the total traded value on that day on NSE spot market. The dotted line shows the date on which co-location facilities were introduced by NSE.



The figure shows that prior the introduction of the co-location facilities in January 2010, AT intensity on the NSE spot market was very low. Less than 20% of the trades (in terms of total traded value) were by algorithmic traders. This picked up substantially after co-location was introduced. The period between January 2010 to July 2011 could be referred as the adjustment period, during which market participants built their infrastructure to utilize the co-location facilities. Post July 2011, the AT intensity in the market saw a sharp surge. The mean value of AT intensity was 50% in 2012, which rose to about 60% in 2013.[13]

To analyse the impact of algorithmic trading, we divide the rest of the analysis into *pre co-lo* and *post co-lo*. *Pre co-lo* is the period when the degree of algorithmic trading on the Indian equity markets was low. The period between January 2009 to Dec 2009 is used

[12]AT intensity is measured as the fraction of total traded value of trades with an AT on atleast one side of the transaction vis-a-vis the total traded value within a certain time interval. Thus, for a stock 'i', in time interval 't', AT intensity ($\textsc{at-intensity}_{i,t}$) is measured as:

$$\textsc{at-intensity}_{i,t} = \frac{\textsc{ttv}_{ATtrade,i,t} \times 100}{\textsc{ttv}_{i,t}}$$

where $\textsc{ttv}_{ATtrade,i,t}$ refers to the total traded value of AT trades in time period 't'. $\text{TTV}_{i,t}$ refers to total traded value of all trades in time period 't'.

[13]Note that this is an overestimation of the AT presence in the market. This is because trades with one side algorithmic trader are also categorized as AT trades. Section A in the appendix shows the intensity when the denominator is adjusted for one side trades.

Table 1 Algorithmic trading presence on the cash market segment of NSE

The table presents AT intensity values on the NSE's spot market. The values are the average values for the pre co-location period (Jan 1, 2009 to December 31, 2009) and the post co-location period (July 1, 2012 to Aug 31, 2013). Each value is first derived for each day and then averaged across all the days. AlgoBoth implies the percentage of trades in which algorithmic trader was present on both sides of the trade. NonAlgoBoth implies the same for trades in which it was a non algorithmic trader on both sides of the trade. AlgoOne represents the percentage of trades on which an algorithmic trader was either on the buy side or the sell side of the trade. All values are represented as a % of total traded value.

	Pre co-lo		**Post co-lo**	
	All	Nifty	All	Nifty
AlgoBoth	0.78	1.04	14.51	20.01
AlgoOne	14.30	17.10	39.62	45.27
NonAlgoBoth	84.94	81.58	45.72	34.11

as the pre co-lo period. *post co-lo* is the period when the degree of algorithmic trading rose substantially, the period between July 2012 to August 2013.

Table 1 provides the break-up of algorithmic trading activity for the sample stocks into percentage of traded value with an algorithmic trader on both sides of the transaction (AlgoBoth), percentage of traded value with an algorithmic trader on only one side (AlgoOne), and percentage of traded value with non algorithmic trader on both sides of the transaction (NonAlgoBoth). The values are shown separately for the Nifty[14] stocks, and for all stocks listed on NSE.

We observe that the level of algorithmic trading went up significantly in the post co-lo period. In 2012-13, roughly about 55% of the trades had an algorithmic traders on at least one side of the transaction. For only the Nifty stocks, this value is even higher to about 65% of all trades.

5.1 The degree of high frequency trading (HFT) on the NSE equity markets

In Section 2, we discussed that not all algorithmic trading is high frequency in nature. Though the data does not give us a direct way to identify a high frequency trader, we use the SEC's definition of a HFT (SEC (2010)) to get an estimate of the level of high frequency trading on the NSE equity markets.

To capture the extraordinarily high-speed and short time frames, we compute the average time span between all order modifications that an order goes through. This is computed at an order level separately for all orders, only algorithmic orders, for algorithmic orders posted by proprietary traders, and for non algorithmic orders. High frequency orders are expected to have very short time frames between order modifications.

Table 2 shows the summary statistics of the average time span between order modifica-

[14]Nifty is the leading market index at the NSE which comprises of the top 50 stocks in terms of market capitalization and liquidity listed at NSE

Table 2 Summary statistics of average time span across modifications

The table reports the summary statistics of the average time span between order modifications for all stocks and for Nifty stocks in the pre and the post co-lo period. Panel 1 reports the values across all stocks while Panel 2 reports the values for Nifty stocks. 'All' indicates summary statistics for all orders, 'algo' for algorithmic orders, 'algo-prop' for algorithmic orders sent by proprietary traders and 'non algo' for non algorithmic orders.

Panel 1: All stocks *(in milliseconds)*

	Min	**Q1**	**Mean**	**Median**	**Q3**	**Max**	**SD**
Pre co-lo:							
All	0.05	45,927	1,665,853	83,755	752,852	21,705,669	3,945,968
Algo	21.55	1,405	168,065	12,140	25,034	20,582,873	1,110,371
Algo-prop	21.87	1,273	16,248	10,875	23,235	10,604,959	59,412
Non algo	0.05	49,865	1,891,483	114,211	1,058,719	21,705,669	4,169,251
Post co-lo:							
All	0.02	72	656,027	1,199	13,910	24,865,635	2,826,220
Algo	0.03	28	20,682	367	2,103	23,546,462	378,783
Algo-prop	0.03	19	3,644	118	947	21,793,576	107,143
Non algo	0.02	10,782	2,666,181	144,682	2,147,474	24,863,241	5,279,783

Panel 2: Nifty stocks

	Min	**Q1**	**Mean**	**Median**	**Q3**	**Max**	**SD**
Pre co-lo:							
All	0.05	42,649	1,183,477	59,953	375,030	21,629,188	3,241,530
Algo	23.60	1,292	104,907	15,225	23,932	20,002,360	835,222
Algo-prop	24.09	1,220	16,088	14,958	22,899	7,010,942	43,445
Non algo	0.06	45,949	1,468,095	81,303	701,200	21,629,188	3,576,364
Post co-lo:							
All	0.02	31	328,255	398	3,089	24,710,983	1,953,984
Algo	0.02	26	10,859	211	1,400	23,077,272	270,524
Algo-prop	0.02	19	2,303	96	687	19,411,924	88,717
Non algo	0.02	6,847	2,192,551	97,220	1,638,676	24,705,349	4,685,968

tions for all stocks, and for Nifty stocks in the pre and the post co-lo period.[15]

We see a sharp drop in average time between modifications in the post co-lo period across all stocks. The median value of time between modifications reduced from 83 seconds to 1 second in the post co-lo period. Within the set of only algorithmic orders, the median value decreased from 12 seconds to 0.3 seconds. For the non algorithmic orders, the median value of average time span **increased** from 114 to 144 seconds. We also note that the first quartile value (Q1) reduced from 45 seconds to 72 milliseconds. Within the algorithmic orders, this value reduced from 1 second to 28 milliseconds. If it is to be believed that HFTs operate in less than 100 milliseconds time frame, we can deduce that less than 25% of all orders are the ones that are originated by HFTs.

The table also shows the summary statistics for the Nifty stocks. The decline in the median value for all orders on Nifty stocks is larger: from 59 seconds in the pre co-lo

[15]In all these computations, we exclude the orders that did not have any activity in terms of modification, cancellation or execution. The average percentage of such orders (for all stocks traded on the NSE) in the pre co-lo period was 64.7%. This reduced to 41.22% in the post co-lo period.

Table 3 Orders to cancellation and orders to trades ratio

The table reports the orders to cancellation ratio (OCR) and orders to trades ratio (OTR) for all stocks as well as for Nifty stocks in the pre and the post co-lo period.

	OCR			**OTR**		
	Mean	SD	Median	Mean	SD	Median
Pre co-lo:						
All stocks	6.69	1.61	6.40	3.85	1.95	3.26
Nifty	7.02	1.44	6.65	2.92	0.77	2.76
Post co-lo:						
All stocks	15.03	53.60	11.03	18.19	40.73	10.25
Nifty	25.81	10.95	25.26	40.56	33.81	29.61

period to 0.3 seconds in the post co-lo period. Less than 25% of the orders undergo modifications in 31 milliseconds on an average.

Another characteristic is high rate of order cancellations. We compute the orders to cancellation (OCR) ratio for all the stocks as well as only the Nifty stocks as the ratio of total number of orders on a stock (whether entered, modified or cancelled) to the total number of cancellations in a day. Table 3 reports the average values of OCR for all stocks as well as Nifty stocks in the two periods. The table also reports the orders to trades ratio (OTR). We observe that for all the stocks, the median value of orders to cancellation ratio increased from 6.40 in the pre co-lo period to 11.03 in the post co-lo period. The orders to trades ratio increased from 3.26 to 10.25. The increase is more pronounced for the Nifty stocks.

6 Are algorithmic traders at an advantage to non algorithmic traders?

This concern relates to algorithmic traders gaining at the cost of non algorithmic traders. There are two arguments related to this concern: a) Due to access to speed, algorithmic traders continuously send orders and clog the order flow pipe. [16] High rare if order flow has potential to crowd out slow or non algorithmic traders who may therefore not be able to send their orders in time. b) Access to speed also provides early informational advantage to algorithmic and high frequency traders. This advantage and increase the adverse selection costs for the non algorithmic traders. It is also argued that algorithmic traders consume liquidity more often than they provide it. The next two subsections test each of these claims.

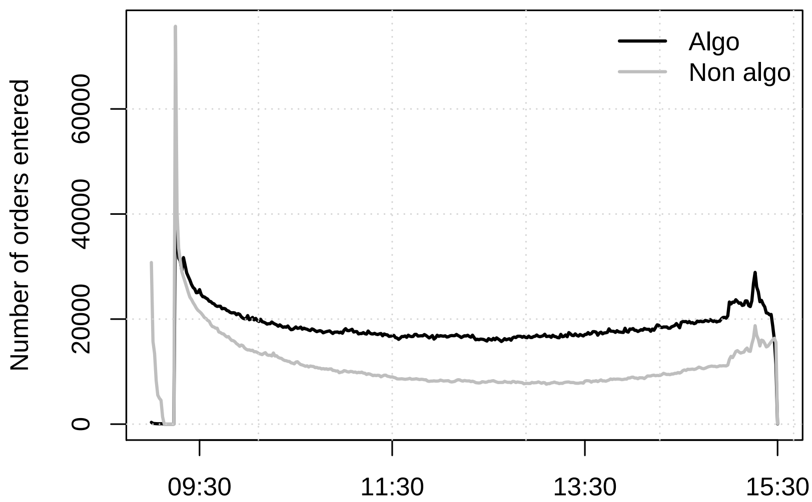
[16]This is referred as quote stuffing.

6.1 Do algorithmic traders crowd out the non algorithmic traders?

To determine if algorithmic traders crowd out the non algorithmic traders, we analyse the number of new orders sent by the two categories within a minute in a trading day. Figure 2 shows the average number of *new* order arrivals per minute on the spot market segment of the NSE equity markets.[17] We restrict this analysis to the period between Jan 1, 2013 to December 31, 2013 when the level of algorithmic trading in the markets was sufficiently high.

Figure 2 Number of new order arrivals per minute on NSE spot market

The figure shows the average number of new order arrivals on the NSE equity spot market in a minute between January 1, 2013 to December 31, 2013. For each day, we first sum the total number of orders in each minute each day, and then average it across all the days during the period.



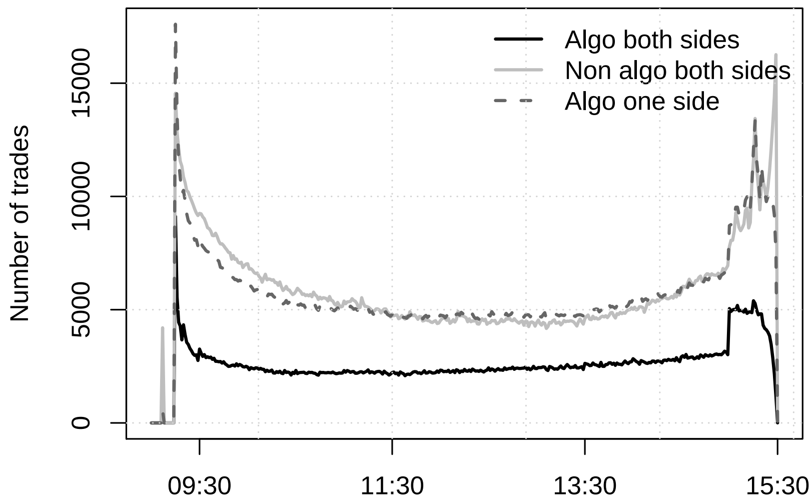
Of the total orders, we observe that about 65% of the new orders that arrive on the NSE equity market are the ones posted by algorithmic traders. In order to examine if this implies that algorithmic traders crowd out non algorithmic traders, we analyse the number of trades in a minute by each category on the spot market. Figure 3 shows the number of trades executed by each category within a minute in a trading day.

The figure shows that about 50% of the trades that are executed every minute are the ones which have non algorithmic trader on both sides of the trade of the transaction. Only about 11% of the trades are the ones which have algorithmic trader on both sides. This is indicative of no crowding out effect of the non algorithmic traders by the algorithmic traders despite a dominating position of algorithmic traders in posting new orders. Thus, we do not see any evidence of non algorithmic traders being at a disadvantage to algorithmic traders when it comes to trade execution.

[17]Note that the figure only shows the number of 'new' order arrivals. We do not take into account modifications and cancellations for this purpose.

Figure 3 Number of trades per minute on NSE spot market

The figure shows the average number of trades executed by the algorithmic and non algorithmic traders in a minute on the spot market. The figure represents the period from July 1, 2013 to December 31, 2013. For each day, we first sum the total number of trades by each category within each minute each day, and then average it across all the days in the sample period.
Algo both sides represents the number of trades in which it was an algorithmic trader on the buy as well as the sell side of the trade. Non algo both sides shows the same for a non algorithmic trader. Algo one side shows the trades on which there was an algorithmic trader on *either* the buy or the sell side of the trade.



6.2 Do algorithmic traders supply or consume liquidity?

To analyse if algorithmic traders supply or consume liquidity, we compute the percentage of trades initiated by algorithmic as well as by non algorithmic traders. A trade is said to be initiated by an AT if he hits a limit order sitting already in the book to execute his own trade. AT's liquidity demand is captured as the percentage of trades that are initiated by an algorithmic trader irrespective of who provides liquidity. Liquidity demand for non algorithmic trader is computed in similar way. We also analyse who supplies liquidity. Four cases are possible: an algorithmic trader provides liquidity to another algorithmic trader, a non algorithmic trader provides liquidity to an algorithmic trader, an algorithmic trader provides liquidity to a non algorithmic trader, and a non algorithmic trader provides liquidity to a non algorithmic trader. We compute the percentage of trades for each of the above cases.

Table 4 shows the summary statistics on liquidity provisioning. On an average, in the post co-lo period, out of the 55.86%[18] trades in which algorithmic traders were present, AT demanded liquidity on 64.03% ($35.77 \times 100/55.86$) trades. This value is similar to the pre co-lo value wherein, out of the total 9.62% of the total trades in which ATs were present, they demanded liquidity on 59% of the trades. For only the Nifty stocks, in the post co-lo period, out of the 72.58% trades in which ATs were present, they demanded

[18]Sum of NON-AT TO AT, AT TO AT AND AT TO NON-AT.

Table 4 Liquidity demand and supply on the spot market

The table presents summary statistics of liquidity provision and consumption by AT and non ATs on the NSE spot market. The values represent the pre and the post co-lo period and are presented for all the stocks listed on the NSE as well only for Nifty stocks. AT-DEMAND indicates the liquidity demanded by ATs while AT-SUPPLY indicates liquidity supplied by ATs.
The values under the "BREAK-UP" show who provided liquidity to whom. NONAT-TO-AT implies the percentage of trades in which non ATs supplied liquidity to ATs, AT-TO-AT shows the percentage of trades in which ATs supplied liquidity to ATs. AT-TO-NONAT shows the percentage of trades in which ATs supplied liquidity to non ATs, while NONAT-TO-NONAT shows the percentage of trades in which non ATs supplied liquidity to non ATs. All values are in terms of % of traded value.

	Pre co-lo			**Post co-lo**		
	Mean	SD	Median	Mean	SD	Median
All stocks						
AT-DEMAND	5.71	1.84	6.26	35.77	4.56	35.54
AT-SUPPLY	4.27	2.04	3.56	36.58	6.76	36.94
BREAK-UP						
AT-TO-AT	0.37	0.25	0.30	16.50	4.27	16.43
AT-TO-NAT	3.91	1.79	3.26	20.08	2.75	20.23
NAT-TO-AT	5.35	1.64	5.87	19.28	1.59	19.43
NAT-TO-NAT	90.38	3.44	90.47	44.15	6.96	43.99
Nifty						
AT-DEMAND	7.99	2.82	8.80	45.70	4.90	46.10
AT-SUPPLY	7.31	3.93	5.65	53.95	6.67	54.59
BREAK-UP						
AT-TO-AT	0.74	0.55	0.54	27.06	5.24	27.12
AT-TO-NAT	6.56	3.39	5.04	26.88	2.39	26.95
NAT-TO-AT	7.24	2.37	7.92	18.64	1.60	18.63
NAT-TO-NAT	85.45	5.92	85.84	27.42	6.13	26.89

liquidity in 62.9% ($45.70 \times 100/72.58$) trades.

On the supply side, in the post co-lo period, AT supplied liquidity in 66.05%($36.58 \times 100/55.38$) of their 55.38% trades. [19] For the Nifty stocks, out of the 72.58% value for Nifty stocks, they supplied liquidity in 74.33% ($53.95 \times 100/72.58$).

To answer the question if algorithmic traders take away liquidity from non algorithmic traders, Table 4 also reports the break-up of who supplies liquidity to whom. Across all stocks, algorithmic traders *consumed* liquidity from non algorithmic trades in 19.28% of the trades in the post co-lo period. These values match with the liquidity supply from ATs to non ATs. ATs supplied liquidity to other ATs in 20.08% of their trades. Within the Nifty stocks, ATs demanded liquidity from non ATs in 18.64% stocks, and supplied liquidity in 18.64% of the trades. The numbers indicate that AT supply as much liquidity as they consume.

[19]Note that the total liquidity demand of 68.34% and supply of 53.65% will not sum to 100. This is because there could be trades in which AT supplied as well as demanded liquidity.

7 Algorithmic traders behavior around stress periods

A key issue that comes up in every debate on high levels of AT/HFT activity is their behavior around stress periods. Critics argue that these traders flee from the market around such periods, when there is really a need to supply liquidity. In this context, we ask two questions:

1. Do algorithmic traders flee from the market during stress periods?
2. Do algorithmic traders increase stress by consuming liquidity from the markets?

To answer these two questions, we undertake a case study and evaluate the behavior of algorithmic traders. Specifically, we examine a recent non informational period which disrupted the Indian equity markets severely: The Emkay crash of October 5, 2012.

7.1 Case Study: The Emkay crash

On the morning of October 5, 2012, while the Indian equity markets opened normally, at around 09:50:52, a trader at the Emkay Global Financial Services, a brokerage firm based out of Mumbai, erroneously punched sell orders worth Rs. 650 crore (approx USD 125 Million) instead of the desired amount of Rs. 34 lakhs (approx USD 65400). The order that was being executed on behalf of an institutional client was a basket order intending the sale of Nifty[20] stocks worth Rs. 34 lakhs to be sold in two tranches of Rs. 17 lakhs each. By mistake, the trader entered the total value of the trade as the quantity of Nifties to be sold and punched orders to sell 17 lakh Nifties.

In a matter of few seconds, Nifty fell from a value of 5767.30 at 09:50:53 to 4997.60 at 09:50:58, a fall of over 10%. As a result of greater than 10% fall, index based market-wide circuit filter got triggered at 09:50:58 and trading was halted. Only the existing orders were executed, during which Nifty fell to intra-day low of 4888.20. Despite the index based market wide filter, trading continued on the derivatives market. After a ten minute halt, at 10:00:22, the spot market entered into the pre open call auction session, which continued for a span of about four and a half minutes. The market resumed into continuous trading at 10:05:00.[21]

Figure 4 gives the full picture of the entire event from the start of the trading in the continuous market to a few minutes after the crash happened. The big drop at 09:50:58 is the time when Nifty dropped over 15% as a result of the fat finger trade. The market reverted to normalcy after the call-auction session.

Figure 5 gives an example of the impact of the trade on a large market cap stock, RE-

[20] Nifty is the leading market index at the NSE which comprises of the top 50 stocks in terms of market capitalization and liquidity listed at NSE

[21] *Communication error at Emkay leads to Rs. 650-crore selloff; Nifty crashes by 900 points*, The Economic Times, October 6, 2012.

Table 5 Timeline of the events on October 5, 2012

The table describes the timeline of events that happened on the morning of October 5, 2012 as a result of the big fat finger trade.

Time Stamp	Event
09:15:00	Markets open normally into the continuous trading session
09:50:58	Nifty dropped from 5767.30 at 09:50:53 to 4997.60, a drop of over 10%. Circuit filter triggered on the spot market
10:00:22	Market re-opened with a pre-open call auction session
10:05:00	Pre-open session ends. Trading resumed
11:17:00	NSE issued first clarification that the circuit filter triggered due to abnormal orders
11:52:00	NSE issued second clarification on the 59 erroneous orders amounting to Rs. 650 crores

LIANCE. It has the second highest weight of 7.68% in the Nifty index.[22] The figure shows the impact of the trade on the prices as well as the total buy and sell orders on RELIANCE. The trade resulted in a fall in the price of RELIANCE from Rs. 855.65 at 09:50:54 to Rs. 682.35 at 09:50:59, a fall of 20%. We also see that the trade wiped out the entire buy side of the limit order book of RELIANCE. Interestingly, we also see that there was a surge in the sell orders at the same time, indicating the increased panic amongst the traders at that point of time. The number of sell orders went up from 260,776 at 09:50:58 to 807,133 at 09:50:59. At 10:05, when the market re-opened after the call auction session, the buy side of the order book started building up. The sell side of the order book also started to revert to previous levels.

We look at the behavior of algorithmic traders on the day of the event: October 5, 2012. We use October 1, 2012 - October 4, 2012[23] as the normal day behavior. We focus on the first two hours of trading for all these days, that is from 9:00 am to 11:00 am. We present the analysis in three sets: a) the stocks that were directly affected as a result of the fat finger trade, b) the Nifty Junior stocks[24] and c) the remaining non CNX 100 stocks.

While it was the Nifty stocks that were directly affected as a result of the fat finger trade, we also examine the set of Nifty Junior stocks and

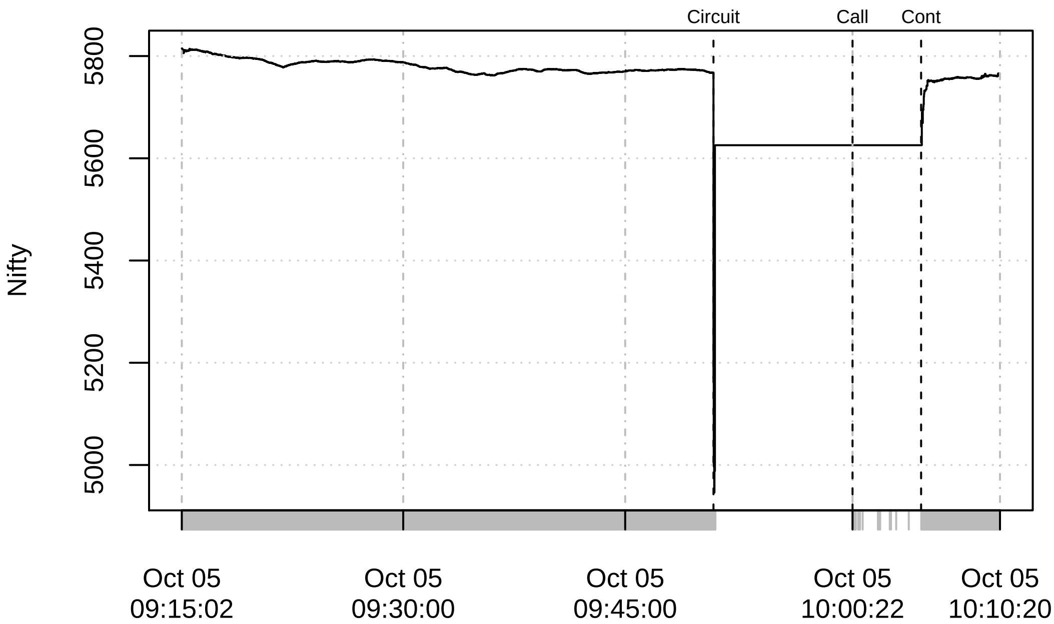
[22]The stock with highest weight in Nifty is currently ITC, 8.21%.

[23]In total, three trading days as October 2, 2012 was a holiday.

[24]This index comprises of the second set of the 50 most liquid securities (after Nifty set) that are traded on the National Stock Exchange. See `http://www.nseindia.com/products/content/equities/indices/cnx_nifty_junior.htm`. Both Nifty and Nifty Junior together form the CNX 100 stock index.

Figure 4 The impact of fat finger trade on Nifty

The graph indicates the behavior of Nifty prior, around and post the event.
The first dotted line indicates the time at which index circuit filter on the equity market was triggered at 09:50:58. The second dotted line indicates the time when the market re-opened into call auction market at 10:00:22. The third dotted line shows the time when trading resumed into the continuous market at 10:05:00.



7.1.1 Do algorithmic traders flee from the markets around stress periods?

To analyse if algorithmic traders flee the markets around the period of Emkay crash, we examine:

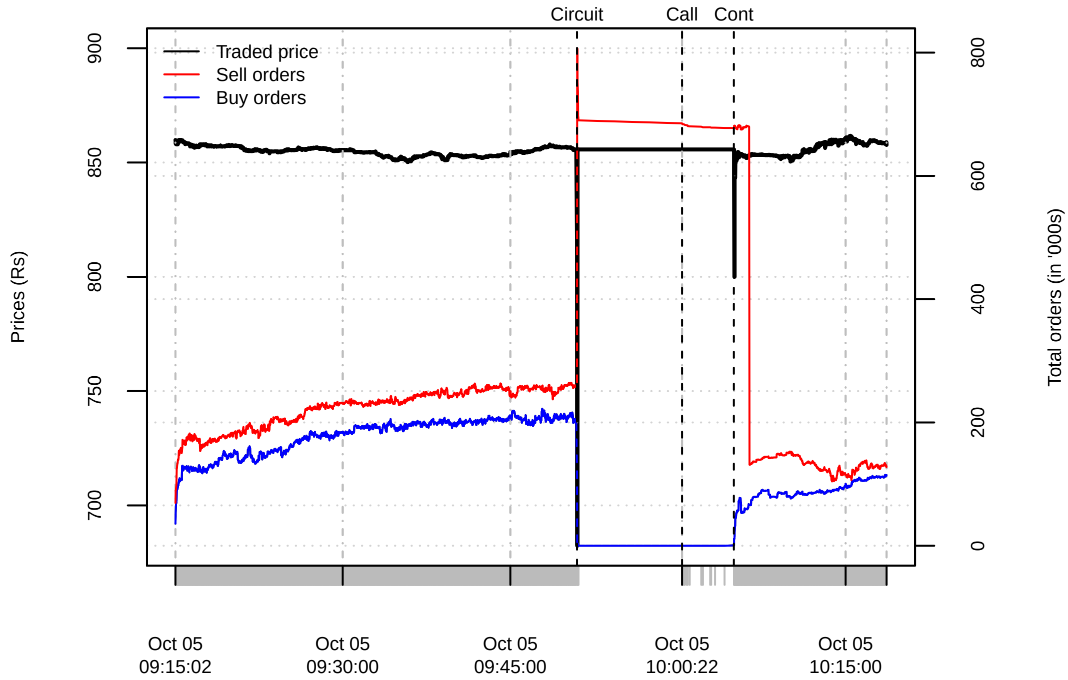
1. Per minute order cancellations by algorithmic traders as a percentage of total orders cancelled.
2. Per minute order entries by algorithmic traders as a percentage of total orders entered.

Figure 6 shows the graph of order cancellations by algorithmic traders on the crash day as well as the 'normal days'. On the day of crash (October 5, 2012), out of the total orders that were cancelled immediately after the markets went into call auction mode, we see that algorithmic traders were responsible for less than 50% of the order cancellations. Once the markets re-opened into the continuous trading, the mean percentage of order cancellations stood at 70%, which is lower than the normal day average of 80%.[25]

[25] Figure 11 in Appendix B shows the same graph for Nifty Junior and non CNX 100 stocks. We see a similar pattern in these two set of stocks. We also analyse the behavior of order modifications by algorithmic traders on the day of crash as well as the 'normal days'. We do not see a significant difference in the behavior of AT around the fat finger trade period vis-a-vis a normal day.

Figure 5 The impact of fat finger trade on RELIANCE

The graph shows the impact of the trade on the prices and order book of RELIANCE, a stock with second highest weight in Nifty.
The first dotted line indicates the time at which index circuit filter on the equity market was triggered at 09:50:58. The second dotted line indicates the time when the market re-opened into call auction market at 10:00:22. The third dotted line shows the time when trading resumed into the continuous market at 10:05:00.



We next analyse the new order entries by algorithmic traders (as a percentage of total number of orders) for a normal day and the crash day. Figure 7 shows the percentage of orders entered by algorithmic traders per minute on Nifty stocks in proportion to the total number of orders. Algorithmic traders contribute to roughly about 60% to the new order entries on a normal day. On the crash day, we see that once the markets re-opened, in the initial few minutes, the algorithmic traders took time in new order entries, but moved to their normal day average within a few minutes.[26]

7.1.2 Do algorithmic traders increase stress by consuming liquidity from the markets?

In order to answer this question, we analyse the liquidity demanded by algorithmic traders from non algorithmic traders on the crash day and on 'normal days'. Figure 8 shows percentage of trades in which algorithmic traders demanded liquidity from non algorithmic

[26]Figure 12 in Appendix B shows the same graph for Nifty Junior and non CNX 100 stocks. We see a similar pattern in these two set of stocks. We also analyse the behavior of order modifications by algorithmic traders on the day of crash as well as the 'normal days'. We do not see a significant difference in the behavior of AT around the fat finger trade period vis-a-vis a normal day.

Figure 6 Percentage of order cancellations by algorithmic traders on the Nifty stocks on the day of Emkay crash and 'normal' days

The graph shows the percentage of orders cancelled per minute by algorithmic traders on the 'normal days' (October 1-4) and on the day of a fat finger trade. Nifty stocks are considered. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

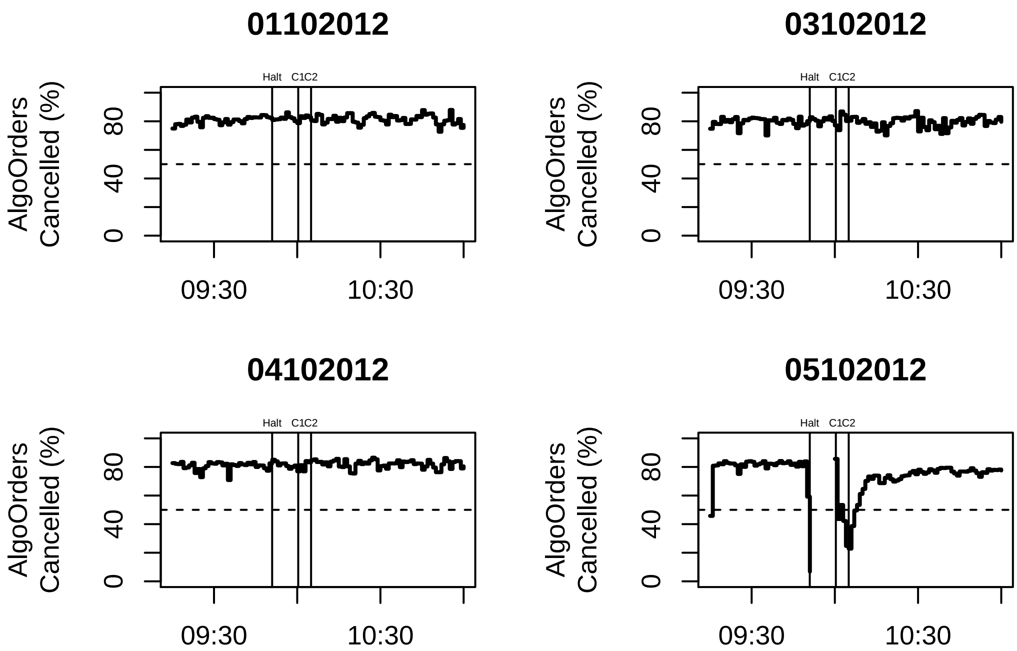


Figure 7 Percentage of order entries by algorithmic traders on the Nifty stocks on the day of Emkay crash and 'normal' days

The graph shows the percentage of orders entered per minute by algorithmic traders on the 'normal days' (October 1-4) and on the day of a fat finger trade. Nifty stocks are considered. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

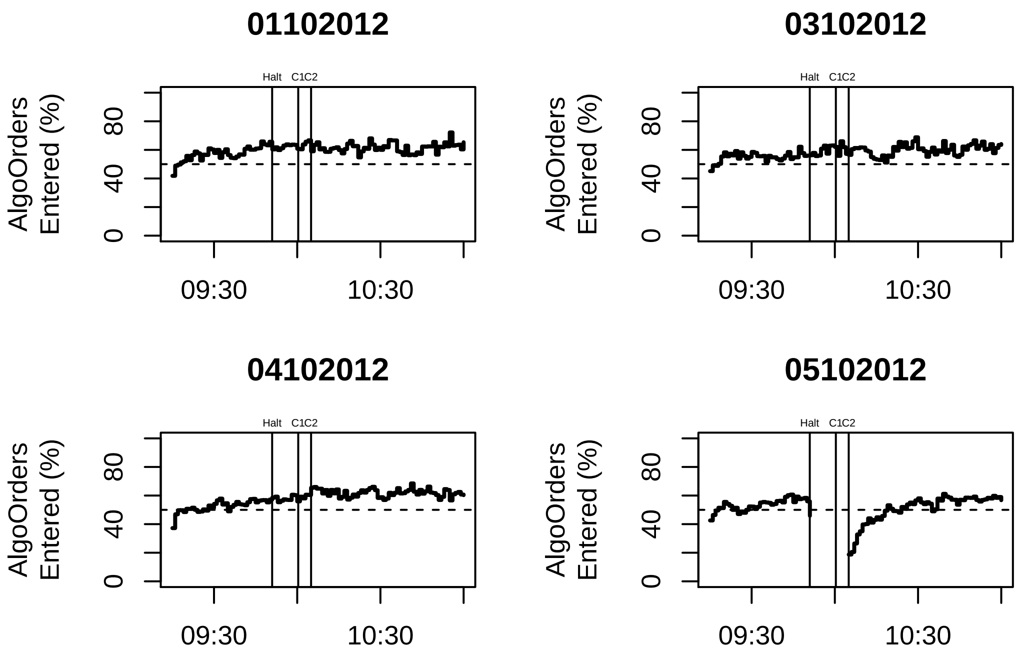
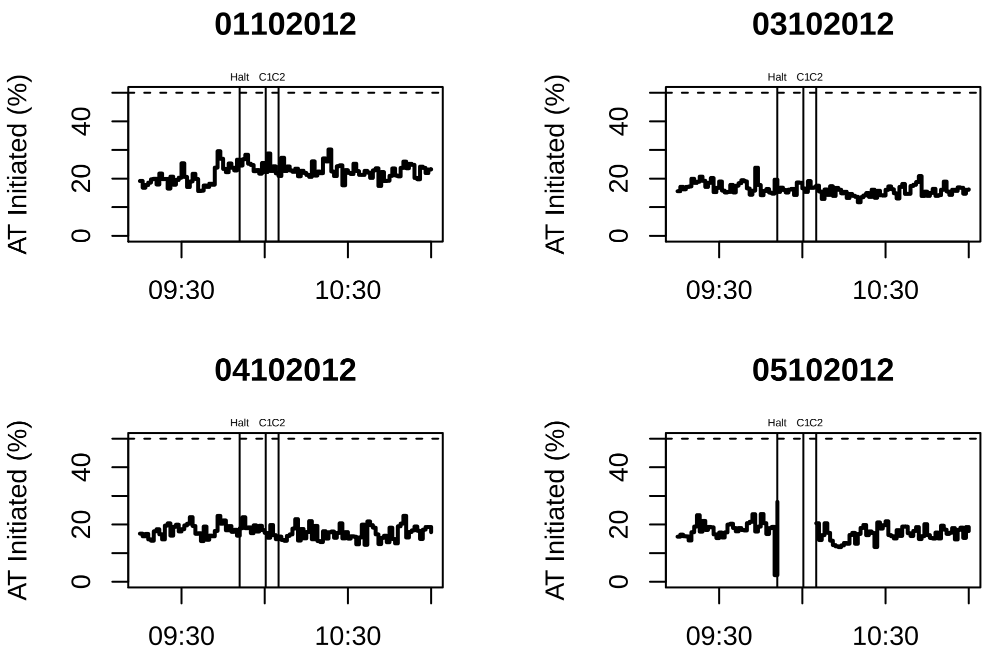


Figure 8 Percentage of trades in which algorithmic traders demanded liquidity on Nifty stocks

The graph shows the percentage of trades in which algorithmic traders demanded liquidity from non algorithmic traders within a minute. It is shown for the 'normal days' (October 1-4) as well as the for the day of fat finger trade for the set of Nifty stocks. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.



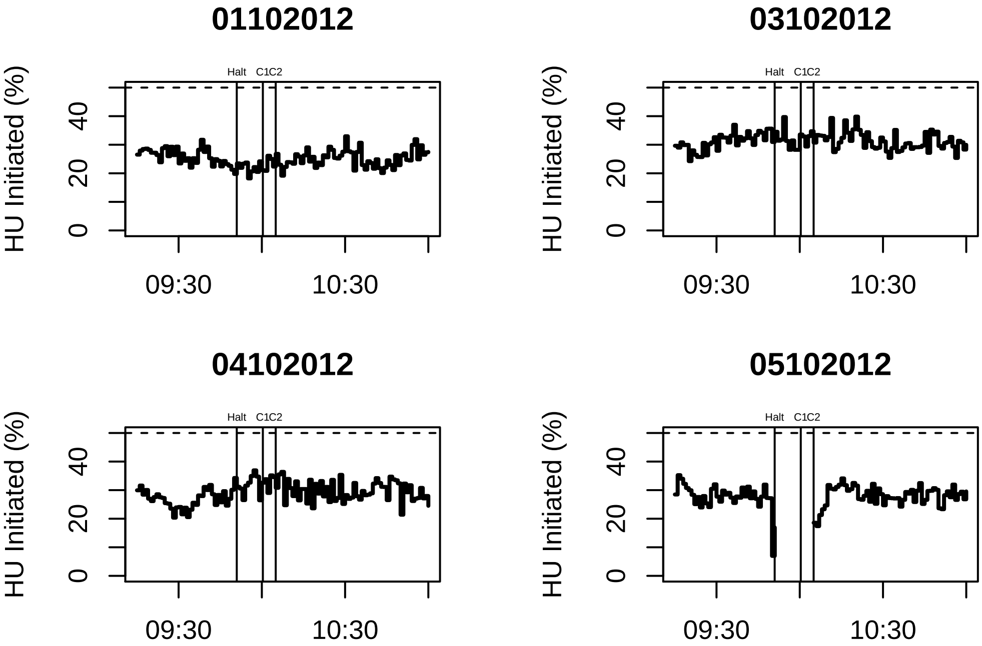
traders [27] on the Nifty stocks. We see that on an average, algorithmic traders liquidity demand from non algorithmic traders varies between 20-30% on normal days. On the day of crash, we see a similar behavior, in both, the pre crash as well as the post crash behavior. Thus, we do not see any evidence of AT's increasing stress around the crash period. In the appendix, we show these graphs for the Nifty Junior stocks as well as the non CNX100 stocks (Figure 14).

Did algorithmic traders provide liquidity to non algorithmic trader? We examine this by studying the pattern of trades where non algorithmic traders sought liquidity from algorithmic traders. Figure 9 shows the percentage of trades where non algorithmic traders demanded liquidity from algorithmic traders. On normal days, in 30% of the trades, non algorithmic traders demand liquidity from algorithmic traders

[27] Liquidity demand is computed in the same way as described in Section 6.2

Figure 9 Percentage of trades in which algorithmic traders supplied liquidity on Nifty stocks

The graph shows the percentage of trades in which non algorithmic traders demanded liquidity from algorithmic traders within a minute. It is shown for the 'normal days' (October 1-4) as well as the for the day of fat finger trade for the set of Nifty stocks. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.



8 Does algorithmic trading improve market quality?

An important concern in the literature is the impact of algorithmic trading on market quality in terms of liquidity, efficiency and volatility. In this respect, we ask the following questions:

a) What impact does algorithmic trading have on the liquidity of the markets?

b) Does algorithmic trading increase price volatility?

c) Does algorithmic trading hamper price efficiency?

Aggarwal and Thomas (2014) examine these questions by comparing the changes in the market quality of stocks that got high levels of AT (*treated* set) after the introduction of co-location with that of the stocks which continued to have lower degree of AT (*control* set). Endogeneity issues are taken care of by using an exogenous event of the introduction of co-location facilities by the exchange in 2010 which directly impacted the level of AT but not market quality. To ensure a like to like comparison, stocks in the treated group are matched with the stocks in the control group based on firm characteristics such as size, price, turnover, floating stock and number of trades. This is done on the period prior

Table 6 DiD regression results from Aggarwal and Thomas (2014)

The table presents the difference in difference (DiD) regression results from Aggarwal and Thomas (2014) who examine the impact of algorithmic trading on market quality. The estimated regression is specified below:

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

where MKT-QUALITY$_{i,t}$ indicates a market quality variable for security 'i' at time 't'. AT$_i$ is a dummy that takes value 1 if i belongs to the treatment group, 0 otherwise. CO-LO$_t$ is a dummy that takes value 1 if t belongs to *post co-lo* period, 0 otherwise. INTRADAY-DUMMY, NIFTY-VOL and LTP are controls for time of the day effects, market volatility and price of the security. The first column in the table is the estimated coefficient (β_3) capturing the effect of algorithmic trading on market quality measures. The second column indicates the expected sign for the hypothesis that AT improves market quality.

	β_3	Expected sign
QSPREAD	-0.35$^+$	$-$
IC	-0.79$^+$	$-$
|OIB|	-13.87$^+$	$-$
DEPTH	0.33	**
TOP1DEPTH	0.16	+
TOP5DEPTH	0.33*	+
|VR-1|	-0.03$^+$	$-$
KURTOSIS	2.76	$-$
RVOL	-2.65$^+$	$-$
RANGE	-16.90$^+$	$-$
LRISK	-0.02$^+$	$-$
TWO-EXCESS	-5.92$^+$	$-$
FIVE-EXCESS	-1.53	$-$
TEN-EXCESS	-0.02	$-$

the introduction of co-location. Once matches for securities in the treated and control group are obtained, the difference in changes in the market quality from the pre to post co-lo period for these two sets are attributed to higher levels of algorithmic trading in these stocks.

Table 6 presents the results from Aggarwal and Thomas (2014). The paper finds that higher levels of algorithmic trading improved the market quality of stocks with higher AT intensity. In comparison to the stocks with low AT, stocks with higher AT experienced a reduction in the transactions costs as measured by quoted spread (QSPREAD) and impact cost IC by about 35 bps[28] and 79 bps respectively on an average. In terms of the number of shares available for trade in the market, the paper finds that DEPTH increased with higher levels of AT. While no significant impact is observed in Rupee depth at the best

[28] 1% is equal to 100 basis points (bps).

bid and ask prices (TOP1DEPTH), the paper finds that cumulated Rupee depth increased for the best five bid and ask prices (TOP5DEPTH) in stocks with higher levels of AT.[29]

A concern often raised about the liquidity provided by ATs is its transitory nature. It is argued that ATs/HFT provide false liquidity which disappears when it is needed the most. In order to test this claim, Aggarwal and Thomas (2014) examine the effect of AT on changes in liquidity risk[30] (LRISK). Transitory liquidity will get reflected by way of high variance in the transactions costs, and therefore high level of liquidity risk. The negative coefficient estimate in Table 6 however suggests that on normal days, stocks with higher AT activity experience *lower* liquidity risk indicating that the AT liquidity is not "false" liquidity.

To determine the impact of AT on price efficiency and volatility, Aggarwal and Thomas (2014) examine the change in variance ratio (|VR-1|) as well as returns volatility (RVOL) for stocks with high AT versus stocks with low AT. The paper finds that contrary to the popular perception, higher level of AT activity reduces volatility in the prices. In addition, prices of the stocks with high AT are more efficient than the stocks with low AT.

Lastly, the paper also examines the effect of AT on extreme price movements. Recent episodes of mini flash crashes in the markets have raised concerns that increased AT/HFT activity is making markets more vulnerable to crashes. It is argued that AT causes higher probability of extreme drops and price reversals over a very short period of time during the trading day which is not beneficial to the markets as a whole (Chordia *et al.* (2013)). This claim is examined by analysing the percentage of extreme price movements over a five minute interval for the high AT and low AT stocks. Extreme price movements are measured as the percentage of deviations in the last traded price from the previous day's closing price in excess of 2%, 5% and 10% (TWO-EXCESS, FIVE-EXCESS, TEN-EXCESS). The paper finds that stocks with high AT experienced *lower* incidence of extreme price movements than the stocks with low AT.[31]

In summary, the paper suggests that AT improves market quality by reducing transactions costs, improving depth, decreasing intraday price volatility and liquidity risk, and reducing the incidence of extreme price movements.[32] These findings do not support the view that is often held against algorithmic trading in the market.

[29]It should be noted that the matched sample of treated and control stocks are primarily the small and medium capitalisation stocks listed on the NSE, indicating that AT works in favor of improving the much needed liquidity for these set of stocks.

[30]It is captured as five minutes variance of impact cost

[31]These findings are similar to a very recent paper by Brogaard *et al.* (2017).

[32]Using similar data from the NSE, Bohemer and Shankar (2014) also examine the impact of AT on the co-movement of order flow, returns, liquidity and volatility. They find that higher AT reduces commonality in all these variables and thus reduces the market's susceptibility to systemic shock.

9 Conclusion

Globally, quantitative research using data from markets where algorithmic trading is a dominant fraction of market trading volume shows that there is no evidence of worsening market quality or increased degree of fraud. The research from the large, global market places have several problems: trading in these jurisdiction is fragmented across multiple markets and has no clear data on whether the orders and trades are generated by algorithmic or non-algorithmic traders. This leads to some sceptisism about the quality of the results.

The Indian equity markets of the National Stock Exchange are less prone to both of these issues, with a fairly aggregated market place and trades and orders data where it is clearly demarcated whether the order placed was from an algorithmic trader and whose orders are part of an executed trade. In this paper, we examine various aspects about how algorithmic trading affects a financial market. These include analysing how much of the equity market trading at the NSE is algorithmic trading (AT); whether algorithmic traders consume liquidity to the detriment of non algorithmic traders; whether algorithmic traders provide liquidity opportunistically and exit the market faster during periods of market stress?; and finally, how does the market quality of a stock with high algorithmic trading intensity compare to one with lower amounts of algorithmic trading.

The evidence here is consistent with what is found in global market places:

1. that the dominance in algorithmic trading appears to indicate a natural progression of the use of technology in the financial market place;
2. that there appears to be as much (if not more) non algorithmic trading in generating trades (which determine market prices). Thus, it is as much the non algorithmic traders that drive prices and price discovery;
3. that when there is market stress as happened during the event of the *Emkay Crash*, the fraction of algorithmic trading does not drop; and
4. that algorithmic trading improves market quality, and that fears about weaker market quality in times of stress is not borne about by empirical analysis. To the contrary, the evidence shows that where there is a sufficiently high degree of algorithmic trading intensity on smaller sized stocks, these have higher market efficiency and more resilient market liquidity than similar sized stocks which algorithmic traders do not choose to trade upon.

This suggests that the question for policy is to analyse and conduct research on what are the features of a stock that encourages a higher degree of algorithmic trading. If such features can be identified, policy research may ideally focus on how these can be emphasised across all stocks in the market so as to uniformly improve the quality of the Indian equity markets.

References

Aggarwal N, Thomas S (2014). "The causal impact of algorithmic trading on market quality." *Technical report*, IGIDR WP 2014-023.

Biais B, Foucault T (2014). "HFT and Market Quality." *Bankers, markets and investors*, pp. 5–19.

Biais B, Foucault T, Moinas S (2015). "Equilibrium fast trading." *Journal of Financial Economics*, **116**(2), 292 – 313.

Bohemer E, Fong K, Wu J (2012). "International evidence on algorithmic trading." *Working Paper.* URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2022034`.

Bohemer E, Shankar RL (2014). "Low latency trading and the comovements of order flow, prices and market conditions." *Technical report.* URL `www.nseindia.com/research/content/BS3.pdf`.

Brogaard J (2010). "High frequency trading and its impact on market quality." *Working Paper.* URL `www.futuresindustry.org/ptg/downloads/HFT_Trading.pdf`.

Brogaard J, Carrion A, Moyaert T, Riordan R, Shkilko A, Sokolov K (2017). "High-frequency trading and extreme price movements." *Working Paper.* URL `http://ssrn.com/abstract=2531122`.

Brogaard J, Hendershott T, Hunt S, Ysusi C (2014a). "High-frequency trading and the execution costs of institutional investors." *Financial Review*, **49**(2), 345–369.

Brogaard J, Hendershott T, Riordan R (2014b). "High-frequency trading and price discovery." *Review of Financial Studies.*

Budish E, Cramton P, Shim J (2014). "Implementation details for frequent batch auctions: Slowing down markets to the blink of an eye." *American Economic Review*, **104**(5), 418–24.

Carrion A (2013). "Very fast money: High-frequency trading on the NASDAQ." *Journal of Financial Markets*, **16**(4), 680 – 711.

Cartea A, Penalva J (2012). "Where is the value in high frequency trading?" *Quarterly Journal of Finance*, **02**(03), 1250014.

Chaboud A, Chiquoine B, Hjalmarsson E, Vega C (2014). "Rise of the machines: Algorithmic trading in the foreign exchange market." *The Journal of Finance*, **69**(5), 2045–2084.

Chordia T, Goyal A, Lehmann BN, Saar G (2013). "High-frequency trading." *Journal of Financial Markets*, **16**(4), 637 – 645.

Foucault T (1999). "Order flow composition and trading costs in a dynamic limit order market." *Journal of Financial Markets*, **2**(2), 99 – 134.

Frino A, Mollica V, Webb RI (2013). "The impact of co-location of securities exchanges and traders computer servers on market liquidity." *Journal of Futures Markets*, pp. 1096–9934.

Golub A, Keane J, Poon SH (2012). "High frequency trading and mini flash crashes." *Technical report*. URL arxiv.org/pdf/1211.6667.

Grossman SJ, Miller MH (1988). "Liquidity and market structure." *The Journal of Finance*, **43**(3), 617–633.

Hagstromer B, Norden L (2013). "The diversity of high-frequency traders." *Journal of Financial Markets*, **16**(4), 741 – 770.

Hasbrouck J, Saar G (2013). "Low-latency trading." *Journal of Financial Markets*, **16**(4), 646 – 679. ISSN 1386-4181.

Hendershott T, Jones CM, Menkveld AJ (2011). "Does algorithmic trading improve liquidity?" *The Journal of Finance*, **66**(1), 1–33.

Hendershott T, Riordan R (2013). "Algorithmic trading and the market for liquidity." *The Journal of Financial and Quantitative Analysis, Forthcoming.*

Hoffmann P (2014). "A dynamic limit order market with fast and slow traders." *Technical Report 1.*

Jones C (2013). "What do we know about high-frequency trading." *Technical report*. URL http://papers.ssrn.com/abstract=2236201.

Jovanovic B, Menkveld AJ (2010). "Middlemen in Limit Order Markets." *2010 meeting papers*, Society for Economic Dynamics. URL http://ideas.repec.org/p/red/sed010/955.html.

Kirilenko AA, Kyle AS, Samadi M, Tuzun T (2017). "The flash crash: The impact of high frequency trading on an electronic market." *Technical report*. URL http://dx.doi.org/10.2139/ssrn.1686004.

Kirilenko AA, Lo AW (2013). "Moore's Law versus Murphy's Law: Algorithmic trading and its discontents." *Journal of Economic Perspectives*, **27**(2), 51–72. URL http://www.aeaweb.org/articles.php?doi=10.1257/jep.27.2.51.

Lee EJ (2013). "High frequency trading in the Korean index futures market." *Journal of Futures Markets*. ISSN 1096-9934.

Malinova K, Park A, Riordan R (2013). "Do retail traders suffer from high frequency traders?" URL http://ssrn.com/abstract=2183806.

Martinez VH, Rosu I (2013). "High-frequency traders, news and volatility." *Working paper*. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1859265.

Menkveld AJ (2013). "High frequency trading and the new market makers." *Journal of Financial Markets*, **16**(4), 712 – 740. URL http://www.sciencedirect.com/science/article/pii/S1386418113000281.

Riordan R, Storkenmaier A (2012). "Latency, liquidity and price discovery." *Journal of Financial Markets*, **15**(4), 416 – 437.

Scholtus M, van Dijk D, Frijns B (2014). "Speed, algorithmic trading, and market quality around macroeconomic news announcements." *Journal of Banking & Finance*, **38**(0), 89 – 105.

SEBI (2013). "Co-location/Proximity hosting facility offered by the stock exchanges." *Technical report*. URL www.sebi.gov.in/cms/sebi_data/attachdocs/1367581007462.pdf.

SEC (2010). "Concept Release on Equity Market Structure." *Technical Report Release No. 34-61358*, Securities and Exchange Commission. URL www.sec.gov/rules/concept/2010/34-61358.pdf.

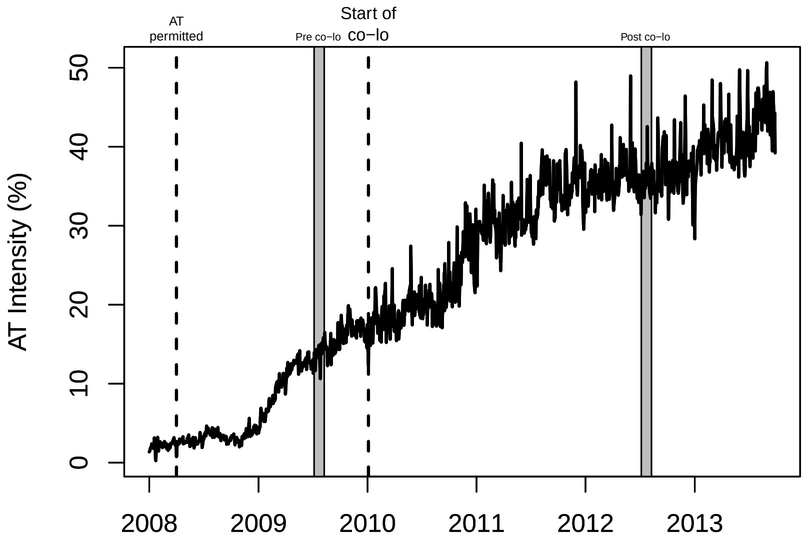
Viljoen T, Westerholm PJ, Zheng H (2014). "Algorithmic trading, liquidity, and price discovery: An intraday analysis of the SPI 200 futures." *Financial Review*, **49**(2), 245–270.

Zhang F (2010). "High-frequency trading, stock volatility, and price discovery." URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1691679.

A AT intensity after adjusting for one-sided trades

Figure 10 AT intensity between 2008 and 2013 with adjusted denominator

The graph shows AT intensity for the overall equity spot market at NSE between 2008 and 2013. AT intensity is measured as a fraction of total traded value of AT trades in a day vis-a-vis the total traded value on that day on NSE spot market. The denominator here is adjusted for the one-sided trades. The dotted line shows the date on which co-location facilities were introduced by NSE. The shaded region indicates the two periods of study.



A trade is called a AT trade if there was an AT on either the *buy* or the *sell side* of the trade or on *both sides* of the trade. Total traded value is however computed as:

$$\begin{aligned} \text{TTV}_{i,t} &= \text{AT-BOTHSIDES}_{i,t} + \text{AT-BUYSIDE}_{i,t} + \text{AT-SELLSIDE}_{i,t} + \\ &\quad \text{NONAT-BOTHSIDES}_{i,t} + \text{NONAT-BUYSIDE}_{i,t} + \text{NONAT-SELLSIDE}_{i,t} \end{aligned}$$

AT intensity, that is, the level of algorithmic trading on a particular stock, is measured as the fraction of total traded value of AT trades vis-a-vis the total traded value within a time interval.

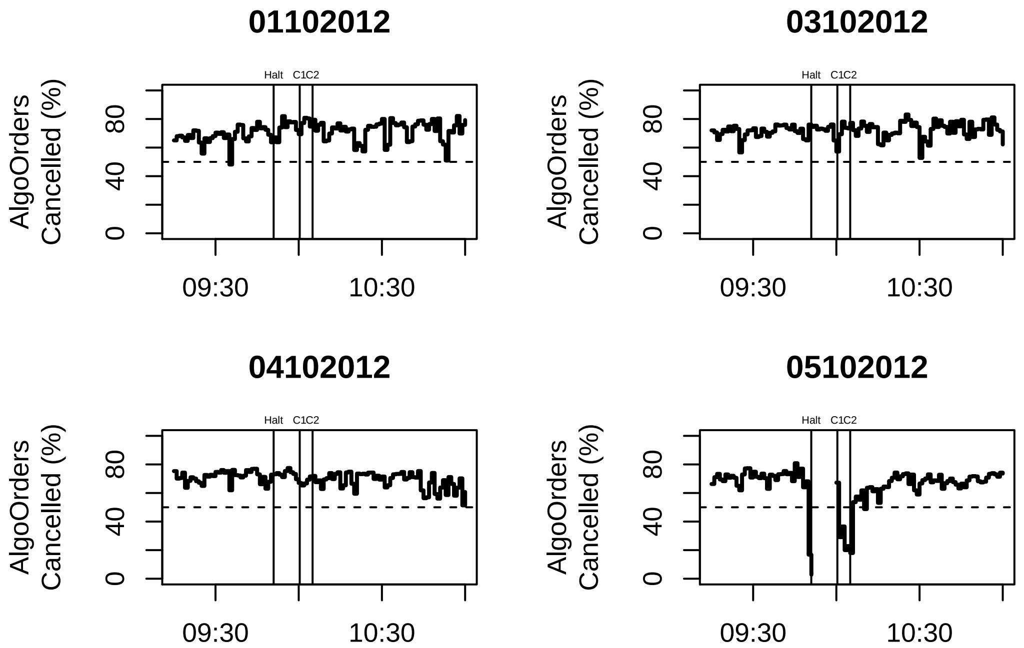
$$\text{AT-INTENSITY}_{i,t} = \frac{\text{TTV}_{ATtrade,i,t} \times 100}{\text{TTV}_{i,t}}$$

B Do algorithmic traders flee the markets around stress periods? AT behavior on the Nifty Junior and non CNX 100 stocks

Figure 11 Percentage of order cancellations by algorithmic traders on the Nifty Junior and non CNX100 stocks on the day of Emkay crash and 'normal' days

The graph shows the percentage of orders cancelled per minute by algorithmic traders on the 'normal days' (October 1-4) and on the day of a fat finger trade. Panel A shows the Nifty Junior stocks. The second panel shows the remaining (non CNX 100 stocks). Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

Panel A: Nifty Junior stocks



Panel B: Remaining stocks

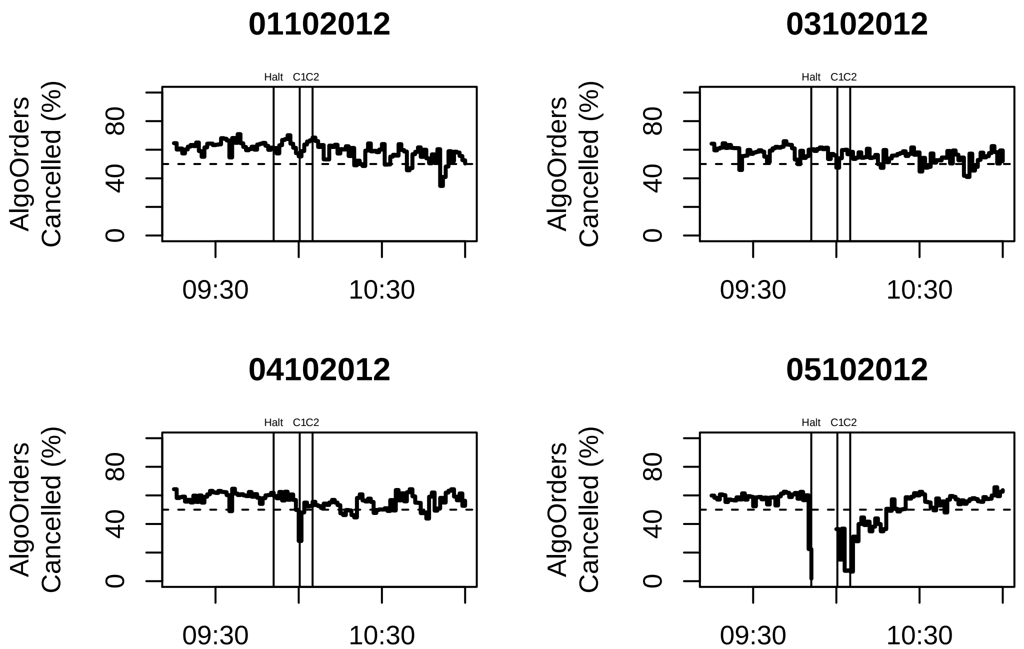
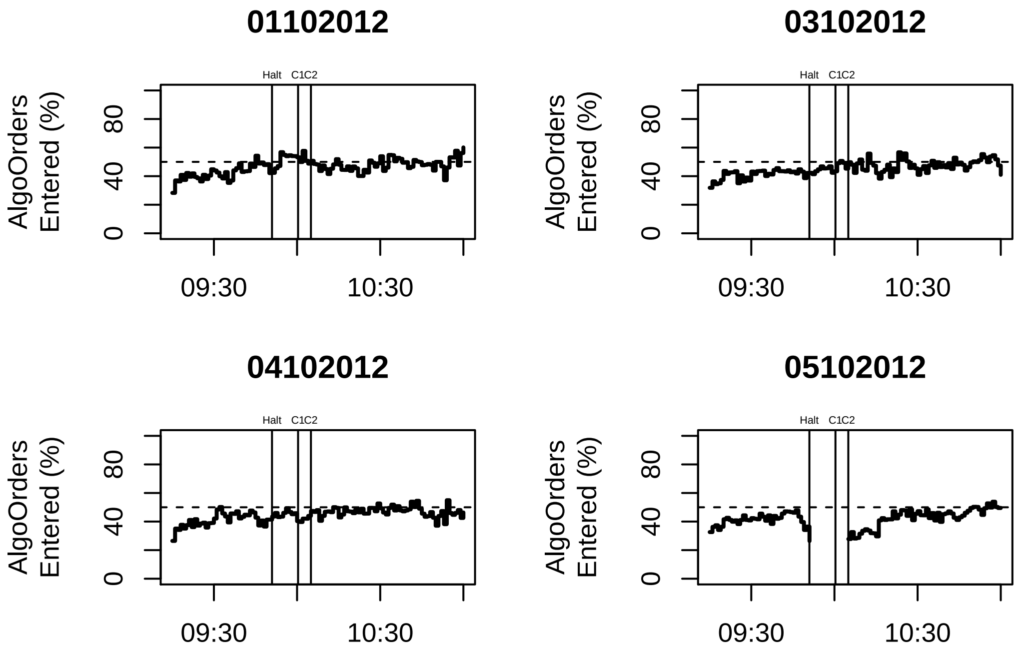


Figure 12 Percentage of order entries by algorithmic traders on the Nifty Junior and non CNX100 stocks on the day of Emkay crash and 'normal' days

The graph shows the percentage of orders entered per minute by algorithmic traders on the 'normal days' (October 1-4) and on the day of a fat finger trade. Panel A shows the Nifty Junior stocks. The second panel shows the remaining (non CNX 100 stocks). Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

Panel A: Nifty Junior stocks



Panel B: Remaining stocks

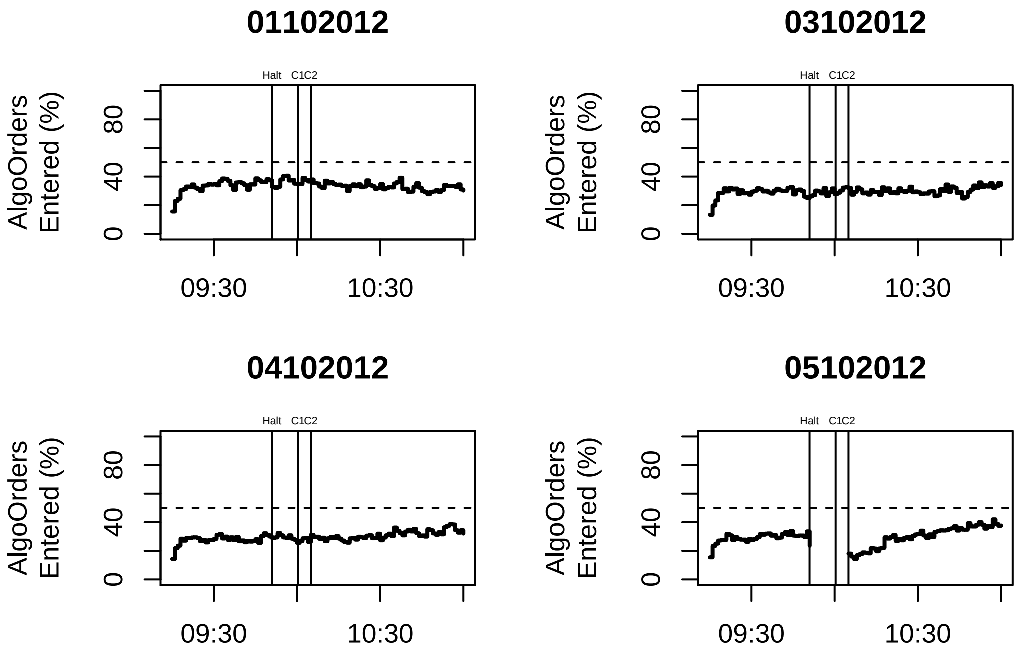
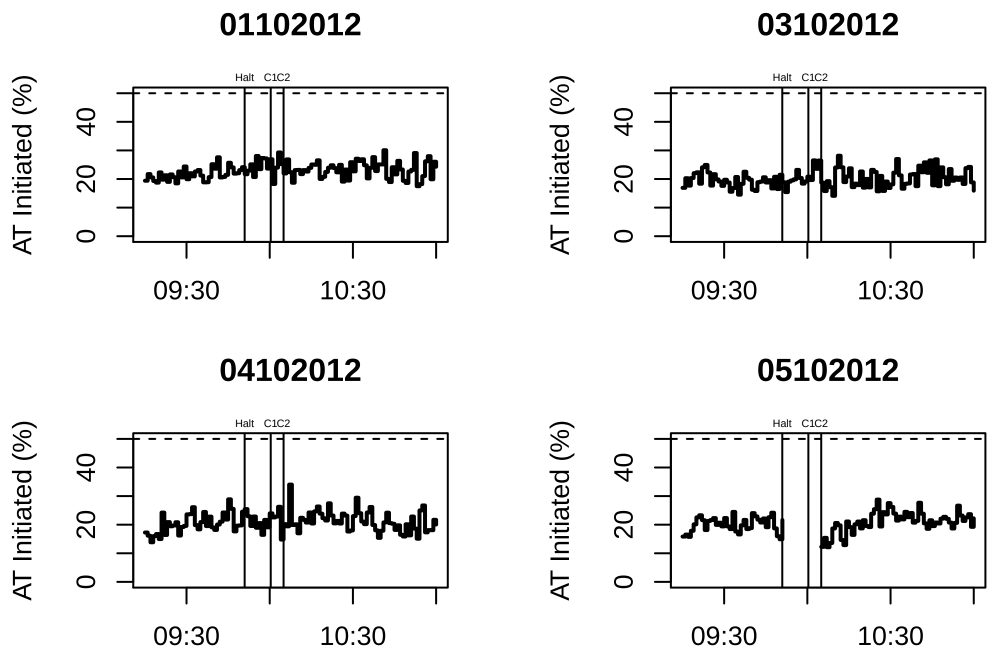


Figure 13 Percentage of trades in which algorithmic traders demanded liquidity on Nifty Junior and the remaining non CNX100 stocks

The graph shows the percentage of trades in which algorithmic traders demanded liquidity from non algorithmic traders within a minute. It is shown for the 'normal days' (October 1-4) as well as the for the day of fat finger trade for the set of Nifty Junior and remaining non CNX 100 stocks. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

Panel A: Nifty Junior stocks



Panel B: Remaining stocks

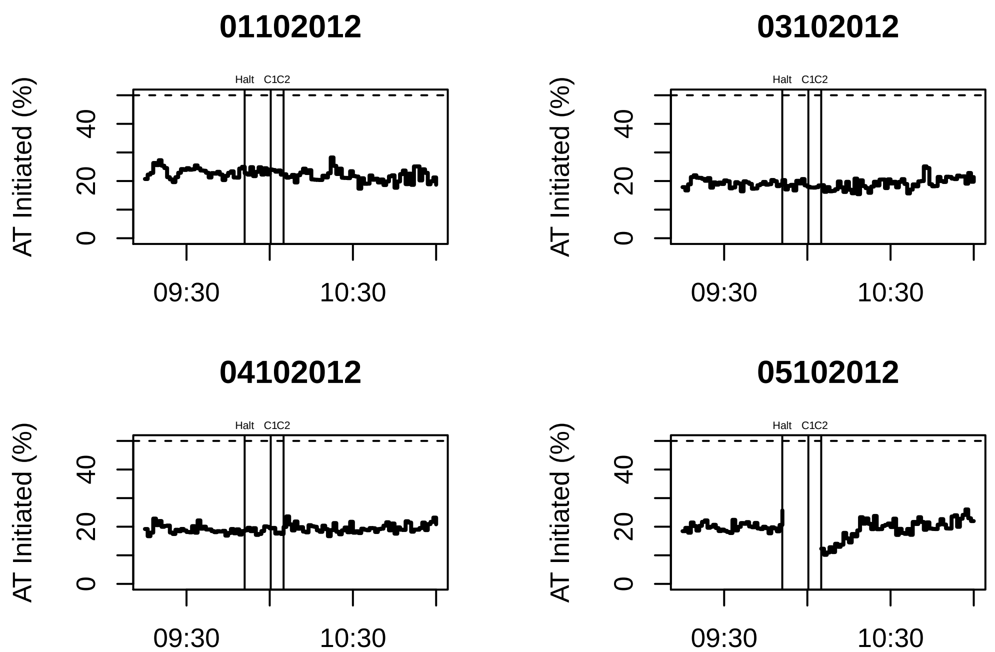
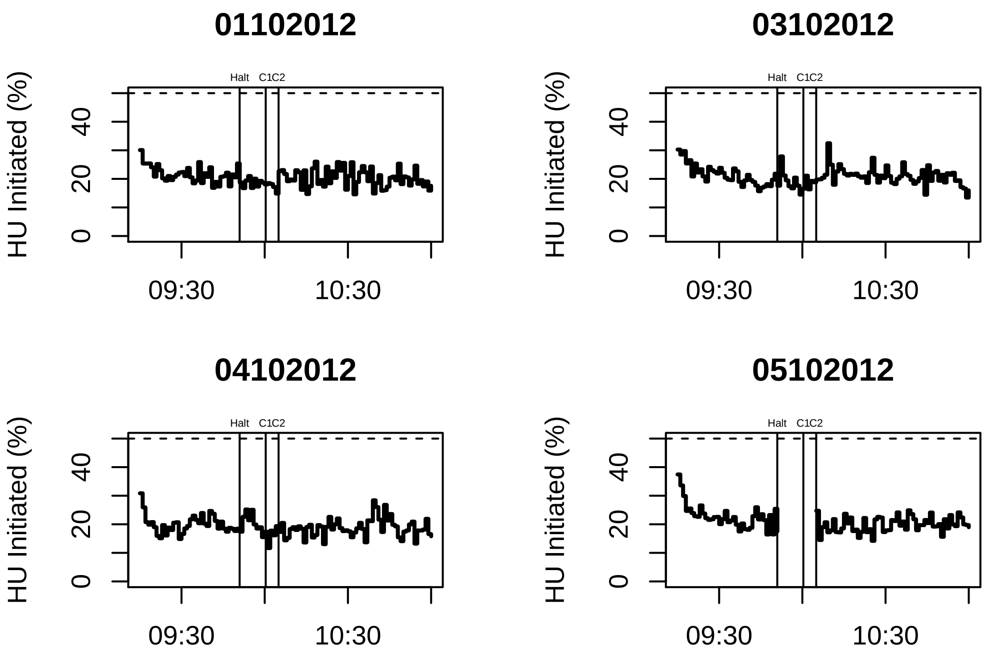


Figure 14 Percentage of trades in which algorithmic traders demanded liquidity on Nifty Junior and the remaining non CNX100 stocks

The graph shows the percentage of trades in which algorithmic traders supplied liquidity to non algorithmic traders within a minute. It is shown for the 'normal days' (October 1-4) as well as the for the day of fat finger trade for the set of Nifty Junior and remaining non CNX 100 stocks. Only the first two hours of trading between 9 am to 11 am are shown in the graph. Halt is the time at which the circuit breaker was triggered on the day of crash: 09:51:00. 'C1' indicates the time when markets entered the call auction mode after the crash at 10:00, and 'C2' indicates the time when markets entered the continuous mode at 10:05.

Panel A: Nifty Junior stocks



Panel B: Remaining stocks