Do regulatory hurdles on algorithmic trading work?

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Abstract

The paper examines changes in market quality surrounding the imposition of an infrastructure usage fee at the National Stock Exchange, a large equity derivatives market by world standards. We analyse two events when the exchange imposed an order-to-trade (OTR) fee: when the exchange introduce the fee in order to reduce load on infrastructure in 2009 (Event 1), and when the regulator increased the fee in order to bring down the incidence of high frequency trading in 2013 (Event 2). Using nonpublic data provided by the exchange, we find that Event 1 resulted in significant lower OTR but also lower market quality, while there was almost no change in either OTR or market quality around Event 2. Despite the doubling, the fee was less binding because of exclusions which effectively limited the applicability of the fee. Our findings show that such interventions tend to be effective only when objectives can be well-defined and measured.

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1 Introduction

In this study, we examine the impact of a regulatory intervention to reduce high frequency trading on the market quality in India. Several studies commissioned by regulators worldwide have recommended OTR fee as one way to slow down HFT (Foresight Report by the U.K. Government, (2012) and MIFID II by the European Commission (2014). The intuition behind such a regulatory intervention is that traders who trade less than the orders they submit might be manipulating markets and/or swamping out other traders from executing legitimate trades. The intervention is intended to prevent their actions from overwhelming the infrastructure of the overall market. The counter-argument is that the fee could stifle trading volume, increase trading costs and adversely impact price discovery roles that are vital to the health and stability of a stock/derivative exchange.

The intervention studied in this paper is a fee on the order-to-trade ratio, called the OTR, and is calculated and implemented by the exchange. At the National Stock Exchange of India Ltd. (NSE), OTR is computed as the ratio of the total number of order submissions, modifications and cancellations (called "order events" in the remainder of the paper) for an order over the number of trades it generates. We examine the effect of two OTR fee events as applied at the NSE: one, when the fee was first introduced on October 1, 2009 on algorithmic trading (AT); and then the subsequent steep increase of the fee that went into effect on May 27, 2013.[1]

Both the initial imposition, and then the subsequent steep increase, of the OTR-based fee, was driven to discourage traders repeated management of their orders through modifications and cancellations without generating trading volume.[2] What differentiates these two events is that the first event was driven more by the exchange to protect load on its infrastructure, while the

[1]See NSE (2009) and SEBIs guidelines on AT vide its circular CIR/MRD/DP/09/2012 dated March 30, 2012. The fee was applicable only on traders in the Indian derivatives markets since AT happens to be more prevalent in the derivatives markets (>50%) than in the cash markets (20%). NSEs main competitor, the Bombay Stock Exchange first introduced its OTR fee only in 2012.

[2]After the fee was introduced in 2009, the NSE has changed the fee three more times till date. It first reduced the fee from July 1, 2010 following the upgrade of its infrastructure before increasing it back again from July 2, 2012 following SEBIs guidelines to a level higher than what it was in 2009. The exchange further doubled its OTR fee from May 27, 2013 following greater regulatory scrutiny of flash crashes in 2012. Furthermore, members who were repeat violators or had highly excessive OTRs were stripped of trading rights for a limited time that apparently were far more costly than the explicit fee that they had to pay under the schedule.

second event was a regulatory response to concerns related to high frequency trading, including the flash crash.[3] Further, while the first event was without exemptions, the second event carried several exemptions in the application of the fee. This allows us to assess the impact of regulatory interventions that are introduced with good intentions but get undermined in practice.

We use a proprietary tick level dataset of all orders and trades in the near month single stock futures for the stocks in the Nifty 50 Index, as of May 2013. Unlike in most major markets, single stock futures are very liquid in the Indian markets and the NSE ranks first globally in notional value traded of these instruments.[4] Our analysis covers a period of four months around each of the two events when the OTR fee was first introduced in October 1, 2009 (Event 1), and raised substantially in May 27, 2013 (Event 2).

We find that the average OTR across the market came down by a statistically significant 20 percent, following the introduction of the OTR fee in Event 1. The OTR reduced for both AT and non-AT. However, the OTR does not change significantly during Event 2, when the fee was increased on regulatory orders. We also find that while the average time between order events increased during Event 1, it remained the same during Event 2. This suggests that the benefits of co-location, and other technological innovations that took place between Event 1 and Event 2, likely outweighed the costs imposed by increasing the OTR fee.

We also examine the OTR intensity for an order as a measure of the load on system infrastructure, where OTR intensity is defined as the ratio of its OTR over the time between modifications. Unlike OTR, the OTR intensity itself went down significantly around Event 1 while it went up around Event 2 for both AT and non-AT orders. This suggests that the fee was binding in reducing infrastructure load during Event 1, but had very little effect in controlling trading strategies during Event 2.

Lastly, we statistically test the impact of the OTR fees using firm fixed effect panel regressions of value-weighted OTR averages as well as OTR intensities across all orders for a given stock for a given day. Stock specific factors and market wide factors act as controls in these regressions. We find that introduction of the fee in Event 1 is negatively correlated with the OTR and OTR intensity. We do not see a similar shift during Event 2. Thus, while the OTR fee had an adverse impact on the active management of limit orders

[3] One of the largest and most scrutinized flash crash event happened on May 6, 2010 in the US when the Dow Jones Industrial Average had its second largest price swing (1,010.14 points) and the biggest one day point decline (998.5 points) in its history.

[4] World Federation of Exchanges (January 2014).

during Event 1, it appears to have been less binding during Event 2, since traders may have well adapted to the new regime by then by trading within the exemptions for the most part. All measures of daily market quality show a decrease around Event 1, with no such effect around Event 2.

This paper adds to the literature on the impact of regulatory interventions to control the effect of algorithmic trading in the financial markets. It is similar in spirit to Friedrich and Payne (2013) but adds to the literature by showing that different interventions have different effectiveness depending upon their objective regarding the effects of algorithmic trading. It is the first paper to show that an OTR fee can be used to reduce the impact of AT on infrastructure usage, but that it may not be as effective to cause desired changes in market quality.

The paper is organised as follows: Section 2 presents the existing literature in this area. Section 3 presents the research context of the Indian markets and regulatory interventions, as well as the questions that we seek to answer in this paper. Section 4 describes the data used for the analysis, Section 5 describes the measurement of trade variables and market quality, and Section 6 describes the methodology used to estimate the impact of the OTR fee. Section 7 presents the results of the analysis, and Section 8 concludes.

2 The impact of algorithmic trading

Several studies report an overall improvement in market quality in the era of algorithmic trading (AT) or high frequency trading (HFT) that there has been significant improvement in virtually all aspects of market quality over time in the US markets (Angel et al., 2011; Robert et al., 2012; Avramovic, 2012). Hasbrouck and Saar (2013) study the effect of low latency (algorithmic) trading over two distinct periods at the NASDAQ and report that higher low latency activity correlates with better market quality. Easley, de Prado and O'Hara (2012) use their VPIN metric as a useful indicator of short term volatility in a HFT world.[5] Hendershott and Riordan (2009) investigate ATs in the Deutsche Borse's Xetra market where ATs can be identified. They find that AT contributes more to the discovery of the efficient price than human trading, and that they do not contribute to excess volatility.[6]

[5]Similar studies include Cumming et al. (2012), Weisberger and Rosa (2013), and Bollen and Whaley (2014)

[6]Chaboud et al. (2013); Brogaard et al. (2014a); Hirschey (2013); O'Hara et al. (2011); Jarnecic and Snape (2014); Gerig (2012); Su et al. (2010); Kirilenko et al. (2014); Backes

The literature also examines the impact of technological improvements on market infrastructure. For example, Hendershott et al. (2011) examine the impact on the NYSE of their auto quoting facility introduced in 2003. They finds that all stocks and in particular for large cap stocks, AT increased liquidity and that an increase in AT results in a reduction in the effective spreads and therefore in investor trading costs. Hendershott and Riordan (2013) focus on the upgrade of the trading system at the Deutsche Borse which led to lower trading latency. They find that liquidity increased while adverse selection and the permanent price impacts were reduced following the upgrade.[7]

In India, Aggarwal and Thomas (2014) examine the impact of AT in India. They find that AT improves liquidity and reduces volatility. Securities with higher AT have lower intra-day volatility of liquidity and lower likelihood of flash crashes.

2.1 Concerns about excessive algorithmic trading

Why is there such discomfort and regulatory concerns about the effect of algorithmic trading, despite this growing body of evidence that AT does not appear to adversely affect market quality? These concerns have moved from debate into implementation at several exchanges including the large U.S. exchanges like NASDAQ and NYSE Euronext. Exchanges globally continue to actively consider such fees inspite of research such as Friedrich and Payne (2013) who show that the OTR penalty imposed by the Italian Stock Exchange has worsened spreads and depth while leaving trading volumes untouched.

Traders who post limit orders provide the market with free trading options Harris and Panchapagesan (2005). These options can be valuable to others but impose a high cost on the submitting trader if they become stale as the market moves away from those orders and they are picked off by other opportunistic ATs. Traditionally, limit order traders have used a variety of strategies including hiding their true order size and pricing away from the market to protect these option values, especially when they are not able to monitor the markets closely. In recent times, the growth in technology, and the resultant reduction in latency, has allowed these traders to protect their

(2011); Menkveld (2013); Andrew et al. (2013); Hagstromer and Norden (2013); Baron et al. (2012); Malinova et al. (2013)

[7] Hendershott and Moulton (2011); and Brogaard et al. (2014b).

orders by modifying and cancelling them easily in light of new information using AT. Without the adverse selection risk, these limit order traders are likely to compete more on price as well as on size. Despite these potential benefits however, several episodes of poorly constructed algorithms and ill-tested systems have brought exchange trading to a halt in the middle of a trading day.

Thus, the institutional response to the rapid rise of HFT comes from two sources. One, regulators worldwide have come to realize the potential of HFT to disrupt markets following flash crashes in several markets including the May 2010 flash crash episode in the US. Two, while exchanges benefit from the higher turnover that HFT brings with them, they also face the cost of technical errors and market closures when their trading systems get overloaded by HFT messaging traffic.

As a result, regulators and exchanges have considered a variety of proposals to charge a fee on HFT for the potential negative externalities that they impose on markets. For example, some have proposed a minimum resting time for orders before any action can be taken on them while others have proposed taxing HFT explicitly for their use of infrastructure or for cancelling orders within a short period.[8] Harris (2013) proposes that the exchange introduces a random delay between order arrival and order processing by the exchange of between 0 and 10 milliseconds. This introduces uncertainty in the latency of order placement and is likely to prevent a monopoly outcome among trading firms, who becoming economically unviable by chasing cutting edge hardware systems in order to reach lowest latency. Some proposals are more stringent such as imposing affirmative obligations for HFT market makers as well as opening up their algorithms to regulators and exchanges in the guise of risk management. Some studies that have examined flash crash episodes do not find HFTs to be the cause of such crashes, but find them to exacerbate the magnitude of these crashes once prices start to fall (Kirilenko et al., 2014). As a consequence, any regulatory or exchange intervention to impose costs on HFT may, therefore, impact market quality, including trading costs and price efficiency.

[8] CME was the first market to institute OTR from April 2005. The fee was computed if OTR exceeded 25:1 original OTR threshold was 25:1.

3 Research questions

In contrast to much of the existing literature which seeks to understand the impact of AT on markets, the current study falls in a relatively unexamined space of research investigating the market and trading environment, when regulators pass fees to curb the incidence of HFT.

In this study, we observe the imposition of one such fee charged on orders in the Indian equity derivatives markets. The fee is charge based on the Orders to Trades Ratio (OTR). We ask two questions:

1. Did the fee have the intended impact of reduction in the orders to trades ratio?
2. Was there an unintended consequence in terms of a deterioration in market quality?

4 Research setting and data description

4.1 The structure of the OTR fee in India

Since the time that AT was permitted in the Indian equity markets, there have been multiple instances when a fee has been charged on the OTR at the National Stock Exchange (NSE). The first of these was in 2009, and was charged by the exchange itself. These have been followed by three other instances: when the fee was reduced by the exchange in July 2010, the fee was re-instated by the regulator, the Securities and Exchanges Board of India (SEBI) in July 2012, and the last when the fee was doubled in May, 2013. Of these, we focus on the first (NSE imposed in 2009[9]) and the last (SEBI imposed in 2013[10]) for our analysis. We choose these two because the variations in the design of the fee across these two events may be useful to identify what makes such a fee effective.

The OTR fee in 2009 that was implemented by the NSE applied to all traders without exceptions. The second event, which remains in force today, was structured by the SEBI and introduced exceptions to the applicability of OTR fee. For instance, all order entries or modifications that are done closer to the market – within one percent of the last traded price – are exempt for

[9] See NSE (2009).
[10] See SEBI (2012), NSE (2013).

the purpose of computing the fee. Similarly, members who are designated as market makers are also exempt from the fee. These exceptions most likely highlight the tradeoffs that exchanges face as they try to maximize their commercial interests without imposing externality costs on the broader market. In both events, the OTR fee was only charged on derivatives orders.

With a larger number of exceptions, one can expect the OTR fee of 2012 to be less binding than it was in 2009. Though we do not have direct evidence about the number of AT members who are market makers some studies suggest that market making is a dominant HFT strategy at other exchanges.[11] If this is true at NSE as well, then most AT orders will be exempt from OTR fee and the exchange no longer has a tool to slow down AT, especially HFT.[12]

4.2 The dataset

Since the OTR fee for both the events was applicable only to trades in the derivative market, we limit our analysis to only derivatives orders and trades. Unlike in most major markets, single stock futures are very liquid in the Indian markets and the NSE ranks first globally in notional value traded of these instruments.[13] Further, to limit our focus to the derivatives that attract the most AT attention, we examine only the near month derivatives of the stocks in the Nifty 50 Index between 2009 and 2013. The contract rollover to the next month is done at two days before expiry to account for shifts in liquidity.

We use a proprietary tick level dataset of all orders and trades in the equity derivatives segment of NSE. In addition to other details regarding the type of order, the dataset has flags on: a) trader type category (whether institutional, proprietary or neither of the two), b) if the order/trade was by an AT or non AT. This allows us to directly identify which orders are AT, which is an advantage compared to much of the existing literature in this field. The dataset also has the flags in the type of order event: entry, modification or cancellation.

The dataset covers a period of 4 months around each of the two events when the OTR fee was either first introduced on October 1, 2009, and then raised

[11] Hagstromer and Norden (2013) find that market making constitute between 63 and 70 percent of HFT trading volume. Kirilenko et al. (2014) use transaction level data to show the HFTs typically act as market makers except during a flash crash.

[12] We are currently working on determining the level of AT market making in NSE.

[13] World Federation of Exchanges (January 2014).

substantially on May 27, 2013. We analyse the orders and trades for four months before and after each event. The periods of our analysis are as follows:

Event 1: Introduction of the fee by NSE.

a) Pre event period: June 2009 to August 2009 (46 trading days).

b) Post event period: October 2009 to December 2009 (42 trading days).

Event 2: Doubling of the fee by SEBI.

a) Pre event period: March 2013 to May 2013 (35 trading days).

b) Post event period: June 2013 to July 2013 (42 trading days).

4.3 Descriptive statistics

Table 1 Sample summary statistics during Events 1 and 2

The table presents the sample summary statistics around the two event periods: October 1, 2009 and May 27, 2013, that respectively mark the introduction and the latest steep revision of the fee on order-to-trade ratio (OTR). The sample universe includes all (near month) equity futures of Nifty stocks in the period between 2009 and 2013.
Each statistic is first computed for each day for a security and then a market cap-weighted average across stocks is taken to arrive at the average value for the day. The market cap-weighted average, as well as the median and standard deviation, are reported across days in a given event period. Daily stock volatility is computed as absolute return using closing prices. Algorithmic trading intensity is defined as the percent of daily traded value that is attributable to algos. Turnover is the total daily turnover across the sample stocks. Similarly for the number of trades and shares traded.
P-values based on student t-test is reported for the averages.

	Event 1			Event 2		
	Pre	Post	p-value	Pre	Post	p-value
Nifty returns (in %)	0.05	0.05	0.99	0.09	-0.08	0.42
Market Cap (in Rs. Bn)	1,189	1281	0.85	1,424	1,449	0.96
Stock volatility (in %)	42.91	33.87	9.27	24.57	24.80	0.96
Shares traded (in Mn)	5.41	4.40	0.00	4,097.70	4,311.18	0.21
Turnover (in Rs. Bn)	3.27	2.84	0.00	2,198.78	2,340.50	0.19
# of Trades (in ‘000s)	7.15	6.68	0.13	6,015.32	6,385.96	0.21
Mean Traded Qty (in ‘000s)	0.96	0.82	0.00	939.77	929.66	0.72
AT-Intensity (%)	18.25	20.34	0.00	64.63	67.62	0.00

Table 1 presents descriptive statistics of the sample stocks for Event 1 and Event 2. All measures are first averaged across stocks for a day using market capitalization weights and then averaged across days. The table shows significant drop in the traded volume as well as the turnover in the period after Event 1. No such impact is seen in the period after Event 2. The AT intensity, which is defined as the percentage of daily traded value that is generated by AT, has more than trebled from around 20 percent in 2009 to around 70 percent in 2013.

Table 2 provides statistics on various order types used as well as on the type of the underlying trader for AT and non-AT orders around Events 1 and 2. All percentages are first computed across orders on a given day for a given stock and then averaged across stocks using market capitalization weights. We report the daily market average across the pre- and post-event periods, and test whether it has significantly changed post-event. Market order usage is less than 2 percent in both event periods as is the usage of stop-loss orders. IOC (Immediate Or Cancel) orders drop significantly for non-AT from 25.5 percent to 3.3 percent after the introduction of OTR fee in 2009. By 2013, the usage of IOC orders among non-algos had fallen to less than 1 percent. On the other hand, AT traders seem to be increasing their usage of IOC orders.

Between 2009 and 2013, there appears to have been a major shift in the preference of AT by proprietary traders. Proprietary orders constitute around 80 percent of all orders in 2009 with AT constituting less than half of them (32 percent out of 80 percent). By 2013, such orders accounted for only 69 percent of all orders with an overwhelming majority of them using AT (65 percent out of 69 percent). The shift in the higher use of AT by proprietary traders can be attributed to the changing market conditions including the availability of co-location services since January 2010. Orders from the trader type, non-proprietary and non-custodian, seem to be increasing after the implementation of the fee and are roughly 20 percent of all orders entered.

4.4 Variation in order submission by participant type

In this section, we discuss the order submission behavior of AT as well as non AT around the two events. Table 3 presents results on the number and percentage of different order events.

An order event can be one of the following: order submission, modification or a cancellation. This is used as the numerator of OTR and is a proxy for the load on infrastructure. For each day, we compute the total number of order events for each security to determine the percentages of various order event categories. We also report the average daily number of order events across securities. The daily average number of order events sharply

Table 2 Sample summary statistics of order characteristics

This table presents the percentages of various types of orders used in the sample period around the two event dates: October 1, 2009 and May 27, 2013, that respectively mark the introduction and the latest steep revision of the fee on order-to-trade ratio (OTR). The sample universe includes all (near month) equity futures contracts of Nifty stocks in the period between 2009 and 2013.
Each statistic is first computed for each day for a security and then a market cap-weighted average across stocks is taken to arrive at the average value for the day. The market cap-weighted average, as well as the median and standard deviation, are reported across days in a given event period. IOC orders are orders sent for immediate fill (full or partial) and would be cancelled otherwise. Orders are considered 'proprietary' if the trader trades on his own account, 'custodian' if he trades on behalf of a customer, and non-proprietary and non-custodian otherwise.
P-values based on student t-test are reported.

As % of orders entered

Variable	**Event 1**			**Event 2**		
	Pre event	Post event	p-value	Pre	Post	p-value
Types of orders						
Market						
AT	0.01	0.19	0.00	0.24	0.24	0.97
Non-AT	0.95	1.54	0.00	0.45	0.36	0.00
IOC						
AT	3.19	3.84	0.13	5.24	7.00	0.00
Non-AT	28.43	3.25	0.00	0.18	0.14	0.00
Stop loss						
AT	0.00	0.00	0.00	0.04	0.04	0.20
Non-AT	0.32	0.49	0.00	0.28	0.22	0.00
Source of orders						
Custodian						
AT	0.03	0.35	0.00	6.4	7.24	0.07
Non-AT	3.62	3.70	0.87	0.74	1.95	0.00
Proprietary						
AT	31.27	34.19	0.00	64.57	63.51	0.15
Non-AT	48.37	35.22	0.00	4.24	3.38	0.00
Non proprietary, non custodian						
AT	2.89	5.47	0.00	18.2	19.81	0.01
Non-AT	13.81	21.07	0.00	5.53	4.10	0.00
# of orders	144,095.17	51,035.78	0.00	124,346.11	151,182.15	0.00

dropped from 0.54 million to 0.28 million after the introduction of OTR in 2009 and is statistically significant. These daily averages tripled in 2013 to 1.8 million, after co-location and other improvements in exchange technology were implemented, which in turn are likely to have facilitated the active management of limit orders.

AT contributed a little more than half of all order events in 2009. This increased to 98 percent of all order events by 2013. Most of these came from proprietary AT orders and suggests that they contribute significantly to the load on infrastructure. The non-AT seem to have reduced their use of infrastructure after OTR fee was first introduced by 3 percent. Though the decrease of 3 percent is small in magnitude, it is statistically significant. The decrease came from a reduced number of cancellations indicating that the exchange was able to partly achieve its desired objective of protecting its infrastructure.

Order submission strategies by AT did not appear to be impacted by Event 1. This may be because AT was a small fraction of the market during this period. However, despite the AT being a dominant source of orders in 2013, the OTR fee change in Event 2 does not appear to have had an impact on the order submission behaviour either. This suggests that the OTR fee, or the way that it was being charged, was perhaps not binding.

Order modifications dominate, accounting for more than 80 percent of all order events in 2013 for AT orders. More than half of these modifications came from orders (mostly proprietary AT orders) that did no trades at all. About 8 percent of all order events come from cancellations of orders with no trades at all.

This suggests that more than half of all infrastructure usage comes from orders that add no value to the price discovery process but can add potential risk to the market. The percentage of trades to the total number of order events is less than 1 percent. If exchanges earn fees as a percentage of trades using which to maintain the quality of their infrastructure, then they need to look for alternate sources of revenue in order to do so.

5 Measurement

An advantage of the work in the paper is that the orders and trades can be precisely identified as originating from AT, and further as originating

Table 3 Sample summary statistics of order submissions

This table presents the percentages of various types of orders events during the sample period around the two event dates: October 1, 2009 and May 27, 2013, that respectively mark the introduction and the latest steep revision of the fee on order-to-trade ratio (OTR). The sample universe includes all (near month) equity futures contracts of Nifty stocks in the period between 2009 and 2013.
An order event can be one of the following: order submission, modification or a cancellation. This is used as the numerator of OTR. Results are reported separately for algo orders and for non-algo orders, as well as for proprietary algo orders. Each cell (other than total events) represents the percentage over all events, and is computed first for each day for a security, then averaged across days for the same security before using market capitalization as weights to average across securities.
P-values based on student t-test are reported.

As % of orders events

Variable	**Event 1**			**Event 2**		
	Pre event	Post event	p-value	Pre	Post	p-value
Percentage of orders entered in a day						
AT	7.79	8.83	0.00	8.88	8.89	0.98
AT Prop	7.12	7.54	0.08	6.39	6.2	0.22
Non-AT	17.83	14.03	0.00	1.17	0.93	0.00
Percentage of orders events in a day by each category						
AT	50.91	53.89	0.01	97.56	97.64	0.56
AT Prop	46.37	45.56	0.42	83.96	82.5	0.03
Non-AT	49.09	46.11	0.01	2.44	2.36	0.56
# of order events	543,556	277,679	0.00	1,532,399	1,805,484	0.00
Percentage modified						
Algo	35.67	36.80	0.24	80.24	80.25	0.98
AT Prop	32.44	30.91	0.07	71.45	70.33	0.12
Non-AT	16.51	22.50	0.00	0.78	0.97	0.10
Percentage cancelled						
AT	7.45	8.27	0.00	8.44	8.50	0.72
AT prop	6.81	7.11	0.20	6.12	5.97	0.33
Non-AT	14.75	9.58	0.00	0.49	0.47	0.21
Percentage modified with no trades						
AT	33.79	34.3	0.57	50.48	48.26	0.00
AT prop	30.81	28.94	0.02	45.29	41.9	0.00
Non-AT	14.70	19.68	0.00	0.61	0.56	0.44
Percentage cancelled with no trades						
AT	7.41	8.22	0.00	8.41	8.48	0.70
AT prop	6.77	7.07	0.21	6.11	5.96	0.34
Non-AT	14.69	9.50	0.00	0.49	0.46	0.24
Percentage executed						
AT	0.40	0.65	0.00	0.50	0.43	0.00
AT Prop	0.37	0.50	0.00	0.29	0.25	0.00
Non-AT	3.69	5.23	0.00	0.77	0.55	0.00

as proprietary trades of brokers. This is useful since standard definitions[14] identify HFT as a combination of proprietary and AT. This helps us to observe the effect of the fee on not just the overall set of AT orders and trades, but also those that are more likely to be HFT.

In the following, we describe in detail how we measure OTR and market quality.

5.1 OTR related measures

For each unique order, we compute the OTR as follows:

$$\text{OTR} = \frac{\#\text{ of order events}}{1 + \#\text{ of trades}}$$

where number of order events include entry, modifications and cancellations. Given the high fraction of orders with no trades in the sample, we add 1 to the denominator of OTR for all orders so as to make the ratio meaningful. The OTR is computed for each order on a stock in a day, and then a value-weighted average is taken.

In order to capture the load on infrastructure better, we also create a new metric called the OTR INTENSITY. It is defined as the ratio of the OTR of an order over its average time between modifications. An order with a high OTR and a very short time between modifications would have high OTR INTENSITY as it would be firing up messages very rapidly. On the other hand, an order with high OTR and a long time between modifications would suggest that orders are responding slowly to changing market conditions and would put little load on the infrastructure.

5.2 Market quality measures

Market quality is captured in terms of the liquidity and the price efficiency of a financial market. Markets with higher liquidity and greater price efficiency in terms of lower volatility and serial correlation are viewed as high quality markets.

We capture the liquidity in terms of *transactions costs* with two measures: quoted spread and price impact. Quoted spread (QSPREAD) captures the cost

[14] The SEC defines HFT as professional traders who act in a proprietary capacity that engage in strategies that generate a large number of trades on daily basis. (Jones (2013))

for a small order by examining the percentage difference between the ask and bid prices while price impact (PRICE IMPACT) measures the instantaneous cost of an average sized order (Rs.250,000) that sweeps the order book. We also use Amihud's illiquidity measure (ILLIQ, Amihud (2002)) to provide a comparison with the rest of the literature.

We also use a set of *depth* measures to capture the liquidity in the limit order book. The dataset allows us to construct depth measures beyond the best prices. We use three measures of depth: rupee depth at best prices (TOP1DEPTH), rupee depth at best 5 prices (TOP5DEPTH), and total average outstanding number of shares at the buy and the sell side (DEPTH). For each stock, we compute each of the above measures at a per second level, and then take the median for the day.[15]

We divide the efficiency related measures into two categories: informational efficiency and volatility. To capture the informational efficiency, we use variance ratio, VR, (Lo and MacKinlay (1988)), computed as the ratio of the variance of 10 minute log returns divided by two times the variance of 5 minute log returns. A value of 1 indicates a random walk. We also use the futures-cash basis (BASIS) computed as the difference between the actual and implied futures price relative to the spot price. The median value of the per second BASIS is used in the analysis.

Amongst the volatility measures, we use realized volatility (RVOL) compared as the standard deviation of five minute returns on a stock. An argument often made against AT is that they withdraw their orders before a trader can act on it. This will get reflected in terms of higher variation in the price impact. Therefore, we also test for changes in the standard deviation of PRICE IMPACT as the volatility of liquidity, LIQRISK. Finally we use basis risk (σ_{BASIS}) as a measure of volatility. It is computed as the standard deviation of basis in a day.

6 Methodology

In order to evaluate the impact of the fee on OTR and market quality measures, we follow two approaches: a) event study analysis and b) multivariate regression.

[15]Except for the ILLIQ, which is a daily measure.

6.1 Event study

In this approach, we analyse the average behavior of each of the OTR and market quality variables in the pre-event and the post-event period. We use an event window of two months which is approximately 44 trading days as the pre event and the post event windows. We then compare and test the difference in the variables using standard statistical tests.

For OTR related measures, we compute the average OTR across all orders for a given stock on a given day, and then take a value-weighted average across stocks using market capitalization weights to obtain the market-wide OTR and OTR intensity for each day in the event window. We test the daily average of both these metrics in the pre- and the post-event period.

For market quality measures, we take a market capitalization weighted average of each variable for each stock in a day, and compare the values in the pre- and the post-event period.

6.2 Regression approach

A simple event study does not control for the presence of endogeniety biases, where factors other than the variable of study could affect the per- and post-event values of the variables of interest. For example, a drop in the OTR after the event could either be because of the fee, or because of changed market conditions (example, lower investor sentiment). In order to isolate the effect of such factors, we use multivariate regression techniques to evaluate the impact of the fee.

6.2.1 Evaluating the impact of the fee on OTR and OTR intensity

In order to capture the change in the level of OTR and OTR intensity after each of the events, we estimate a firm fixed effects regression specified below:

$$\begin{aligned}\text{OTR}_{i,t} &= \alpha_i + \beta_1 \times \text{FEE-DUMMY}_t + \beta_2 \times \text{AT-INTENSITY}_{i,t} + \beta_3 \times \text{MCAP}_{i,t} + \\ &\quad \beta_4 \times \text{INVERSE-PRICE}_{i,t} + \beta_5 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where the dependent variable, OTR $\in$ (VWTD-OTR, VWTD-OTR INTENSITY). $\text{OTR}_{i,t}$ denotes the OTR related measure for stock 'i' on day 't'. FEE-DUMMY_t

is the event dummy which takes value 1 for the post-event period, 0 otherwise. AT-INTENSITY$_{i,t}$ captures the level of algorithmic trading on stock 'i' on date 't'. MCAP$_{i,t}$ denotes the logarithmic value of the market capitalization of stock 'i' on date 't', and is used to control the size and degree of information asymmetry present in a stock's price. INVERSE-PRICE$_{i,t}$ denotes the inverse of the price of the stock 'i' on date 't', and is used as a measure for relative tick size. NIFTY-VOL$_t$ denotes Nifty index volatiliity on day t, and is used as a control for daily variations in market volatility.

We estimate the model using firm fixed effects so as to control for other unobserved firm specific factors. All variables are winsorized at 1 percent and 99 percent for estimation that is robust to outliers.

The coefficient of interest is β_1 which captures the change in the level of OTR measure in the pre and the post event period after controlling for other factors. We test for the hypothesis:

$$H_0 : \beta_1 = 0$$
$$H_1 : \beta_1 < 0$$

If the fee was effective in reducing the orders to trades ratio, the null of $\beta_1 = 0$ will be rejected.

6.2.2 Evaluating the causal impact of the fee on market quality

Since the fee is implemented only on the derivatives market, we use the related cash market to set up neat empirical design to evaluate the causal impact on the market quality variables using a difference in difference (DID) regression. Here, the value of the market quality variable of the stock on the spot market can be used as the *control*, while that on the single stock futures can be used as the *treatment*. We then estimate the following DID regression:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} \;=\;& \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE-DUMMY}_t + \\ & \beta_3 \times \text{TREATED}_i \times \text{FEE-DUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ & \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ & \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where MKT-QUALITY$_{i,t}$ is a market quality variable described in Section 5.2. TREATED$_i$ is a dummy variable which takes value 1 for data related to the futures market, and 0 for the cash market. FEE-DUMMY$_t$ is the fee dummy which takes value 1 for post event dates, and 0 otherwise. TREATED$_i$ $\times$

FEE-DUMMY_t is the interaction term between the fee dummy and treated dummy. The remaining are control variables as described in Section 6.2.1.

In the DID regression, β_1 captures the average difference between the level of the dependent variable on the futures and the cash market. β_2 captures the average value in the dependent variable arising out of the differences in the two time periods. β_3 which captures the difference in the level of market quality variable on the futures and the cash market after the fee implementation is the coefficient of interest that measures the causal impact of the OTR fee. We test for the hypothesis:

$$
\begin{aligned}
H_0 &: \beta_3 = 0 \\
H_1 &: \beta_3 \neq 0
\end{aligned}
$$

where if $\hat{\beta}_3 = 0$, will indicate that the fee had some impact on the market quality variable.

6.2.3 Evaluating the impact of the fee on basis and basis risk

Since BASIS and σ_{BASIS} are computed using the futures and cash market data, a DID regression can not be used to evaluate the impact of the fee. We therefore use a firm fixed effects regression to measure the impact of the fee on these two variables. The regression is specified below:

$$
\begin{aligned}
\text{INFO-EFFICIENCY}_{i,t} = {} & \alpha_i + \beta_1 \times \text{VWTD-OTR}_{i,t} + \beta_2 \times \text{FEE-DUMMY}_t + \\
& \beta_3 \times \text{VWTD-OTR}_{i,t} \times \text{FEEDUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\
& \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\
& \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}
\end{aligned}
$$

where $\text{INFO-EFFICIENCY}_{i,t} \sim (\text{BASIS}, \sigma_{\text{BASIS}})$ for stock 'i' on date 't'. $\text{VWTD-OTR}_{i,t}$ denotes the value weighted average OTR on stock 'i' on date 't'. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{VWTD-OTR}_{i,t} \times \text{FEEDUMMY}_t$ is the interaction term between the value weighted average OTR and fee dummy. Rest of the explanatory variables are control variables, as described in Section 6.2.1.

The coefficient, β_3 captures the change in the dependent variable as a result of a unit change in value weighted OTR conditional on the post event time period. We test for the null hypothesis:

$$H_0 : \beta_3 = 0$$
$$H_1 : \beta_3 \neq 0$$

If the event did not have any impact on basis or basis risk, the null of β_3 will not be rejected.

7 Results

7.1 Event study analysis

7.1.1 Impact of the fee on OTR and OTR intensity

Table 4 presents the event study results of daily average market-wide OTR around the two event periods. We also report median, minimum and maximum OTR along with the daily standard deviation of the OTR. Panel A-D present the results for all orders, AT orders, non-AT orders and proprietary AT orders respectively.

Following the introduction of OTR fee, the average market-wide order OTR came down from 4.87 to 4.10, a decline of around 15 percent that is statistically significant. Both AT and non-AT OTRs came down significantly with the magnitude being roughly the same.

Not surprisingly, OTR for a typical AT order (as well as for a proprietary AT order) is almost three times the OTR level for a typical non-AT order. Haferkon et al. (2013) document that AT orders have an OTR of 10 which is twice that of non-AT traders in DAX 30 stocks traded at the Deutsche Borse. The maximum OTR for non-AT orders is higher than the maximum threshold suggested for fee computation indicating that non-AT traders also use the system heavily.

The OTR after Event 2 declined marginally, but the difference is statistically significant only for the algo proprietary category of orders. It could be either because of the fee or because of other factors. The fact that OTR did not change significantly in 2013 when the fee was higher than what was introduced in 2009 indicates that the fee did not serve the purpose of controlling the behavior of AT traders.

Table 4 Summarising daily OTR before and after Event 1 and Event 2

This table presents the distributional characteristics of 'order-to-trade' ratio (OTR) during the sample period around Event 1 and Event 2. The sample includes all (near month) equity futures contracts of Nifty stocks.
Panels A-D presents the results for the overall sample, as well as separate results for algo orders, non-algo orders, and proprietary algo orders.
Panel E presents the percentage of proprietary algo orders that exceed OTR thresholds used by NSE for computing its fee.
p-values based on student t-test for the averages and from a Kolmogorov-Smirnov test for the medians are reported.

	Event 1			**Event 2**		
	Pre	Post	p-value	Pre	Post	p-value
Panel A: All Orders						
Average	4.87	4.1	0.00	7.28	7.04	0.12
Median	2	1	1	2	2	1
Min	0.01	0.01		0.01	0.01	
Max	14,017	21,328		188,032	550,287	
SD	0.72	0.39		0.75	0.66	
Panel B: AT Orders						
Average	7.81	6.58	0.00	7.80	7.49	0.09
Median	2	2	0.00	2	2	1
Min	0.04	0.02		0.01	0.01	
Max	14,017	10,994		188,032	550,287	
SD	1.73	1.04		0.90	0.76	
Panel C: Non-AT Orders						
Average	3.12	2.83	0.00	1.77	2.04	0.01
Median	2	2	1	1	1.50	0.00
Min	0.01	0.01		0.01	0.01	
Max	8,455	21,328		7,669	52,116	
SD	0.54	0.20		0.24	0.64	
Panel D: AT prop orders						
Average	7.82	6.59	0.00	8.78	8.27	0.04
Median	2.38	2	0.00	2	2	1
Min	0.04	0.02		0.01	0.01	
Max	10,515	10,994		188,032	550,287	
SD	1.59	1.02		1.19	1.05	
Panel E: % of AT Prop orders > than pre-defined thresholds						
>50	1.87	1.56	0	4.64	4.48	0.34
>100	0.55	0.53	0.58	3.04	2.97	0.66
>250	0.09	0.11	0.3	0.54	0.55	0.33
>500	0.03	0.03	0.79	0.24	0.26	0.01

Panel E of the table indicates the percentage of orders that violate the thresholds used in the computation of OTR by the exchange. The percentage of these orders in 2009 and in 2013 remains small.

Table 5 shows the impact of the fee on OTR INTENSITY for all the four categories of orders: all, algo, algo prop and non algo. The table shows that AT orders have higher intensity than non-AT orders though the difference has amplified in 2013 compared to 2009. The average OTR intensity for AT orders is around 85 as compared to 7 for non-AT orders in 2013., Unlike OTR, the OTR intensity has gone down significantly in Event 1 while it has gone up in Event 2 for both AT and non-AT orders. This suggests that the fee was binding in reducing infrastructure load in 2009 but had very little effect in controlling trading strategies in 2013.

7.1.2 Impact of the fee on market quality

Table 6 presents the results of the event study analysis for each market quality measure described in Section 4.2. Both measures of transactions costs indicate a substantial increase in quoted spread as well as price impact post Event 1. This suggests that OTR fee altered the incentives of market making orders as seen by Freiderich and Payne (2013) in the Italian market. However, there is no difference in these metrics before and after Event 2.

Depth related measures indicate a mixed impact of Event 1. While the average total depth in the market deteriorated, depth at the best prices (TOP1DEPTH) and at the five best prices (TOP5DEPTH) increased. This could have been the result of either an increase in the average price level, or because of the increase in the number of shares. Despite the exemption by the exchange to market makers, we see a fall in all three measures of depth.

It should be noted here that OTR fee applied to all AT, including market making AT, in Event 1 but did not apply to market makers in Event 2. The results above are however contrary to the expected behavior and need further investigation by way of regression techniques.

Information efficiency measures, VR as well as BASIS did not see any impact due to either of the events, indicating that there was no impact on price efficiency. Amongst the volatility measures, while price risk show a statistically significant decline, basis risk (σ_{BASIS}) as well as LIQRISK saw a significant increase after Event 1, which is a negative for market efficiency. No such impact is seen post Event 2.

Table 5 Summary statistics of daily OTR intensity

This table presents the distributional characteristics of OTR intensity during the sample period around Event 1 and Event 2. The sample universe includes all (near month) equity futures contracts of Nifty stocks in the period between 2009 and 2013.
The daily average (and median, minimum and maximum) of the market's OTR Intensity is reported for each event period.
p-values based on student t-test for averages and Kolmogorov-Smirnov test for the medians are reported.

	Event 1			**Event 2**		
	Pre	Post	p-value	Pre	Post	p-value
All orders						
Average	1.71	1.24	0	79.08	121.34	0
Median	1.42	1.06	0	13.64	33.77	0
Min	0	0		0	0	
Max	12,599	91,954		132,882,613	17,373,675	
SD	0.29	0.23		12.05	44.09	
AT orders						
Average	3.08	2.39	0	84.97	131.6	0
Median	2.04	1.81	0	16.11	38.48	0
Min	0	0		0	0	
Max	12,599	13,041		13,288,261	17,373,675	
SD	0.58	0.57		13.29	47.86	
Non-AT orders						
Average	0.81	0.64	0	6.14	10.96	0
Median	0.49	0.59	0	0.05	0.08	0
Min	0	0		0	0	
Max	11,094	91,954		10,460	660,140	
SD	0.22	0.13		3.82	7.98	
AT prop orders						
Average	3.12	2.42	0	97.46	151.87	0
Median	2.03	1.75	0	15.85	40.52	0
Min	0	0		0	0	
Max	5,638	13,041		13,288,261	17,373,675	
SD	0.56	0.56		16.42	59.47	

Table 6 Event study results for market quality variables

This table presents the market cap weighted averages of market quality measures around the two event dates: October 1, 2009 and May 27, 2013, that respectively mark the introduction and the latest steep revision of the fee on order-to-trade ratio (OTR). The sample universe includes all (near month) equity futures contracts of Nifty stocks in the period between 2009 and 2013. For Event 1, the pre-event period covers June to August 2009 while post-event period covers October to December 2009. Similarly for Event 2, the pre-event period covers March to May 2013 while post-event period covers June and July 2013. The market quality measures are described in Section 5.2. P-values of the student t-test statistic is reported.

	Event 1			**Event 2**		
	Pre	Post	p-value	Pre	Post	p-value
QSPREAD (%)	0.06	0.21	0.00	0.03	0.03	0.17
PRICE IMPACT (%)	0.06	0.22	0.00	0.03	0.03	0.26
DEPTH (# of shares) (in '000s)	242.29	89.17	0.00	279.32	254,79	0.05
TOP1DEPTH (Rs. '000s)	968.64	1,260.17	0.00	848.96	829.50	0.02
TOP5DEPTH (Rs. Mn)	6.64	7.32	0.01	6.66	6.29	0.01
VR	0.89	0.89	0.88	0.90	0.90	0.59
BASIS (%)	-0.21	-0.29	0.35	-0.11	-0.25	0.22
RVOL (%)	45.87	31.98	0.00	25.02	26.17	0.10
LIQRISK (%)	0.02	0.11	0.00	0.02	0.02	0.30
σ_{BASIS} (%)	0.11	0.62	0.00	0.13	0.09	0.37

In summary, the event study results indicate that while Event 1 had a statistically significant impact in terms of reduction in OTR and OTR intensity, there was also a negative impact on the transaction costs and volatility measures of market quality. Results on depth and price risk measures of volatility run counter to the intuition, and it could be that there were other factors at play which caused such statistical changes in these measures. In the next section, we control for these other factors and assess the impact of the fee.

7.2 Regression analysis

7.2.1 Impact of the fee on OTR and OTR intensity

In this section, we discuss the results of the regression estimations described in Section 6.2.2. Table 7 shows the panel regression estimates of OTR and OTR intensity on a set of control variables as well as a fee event dummy variable. As seen in the event study results, the introduction of fee in 2009

Table 7 Regression results of OTR and OTR intensity

The table presents the fixed effects regression estimates on OTR measures for Events 1 and 2. The regression is specified as:

$$\begin{aligned}\text{OTR}_{i,t} &= \alpha_i + \beta_1 \times \text{FEE-DUMMY}_t + \beta_2 \times \text{AT-INTENSITY}_{i,t} + \beta_3 \times \text{MCAP}_{i,t} + \\ &\quad \beta_4 \times \text{INVERSE-PRICE}_{i,t} + \beta_5 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where the dependent variable, OTR $\in$ (VWTD-OTR, VWTD-OTR INTENSITY). $\text{OTR}_{i,t}$ denotes the OTR related measure for stock 'i' on day 't'. FEE-DUMMY_t is the event dummy which takes value 1 for the post-event period, 0 otherwise, $\text{AT-INTENSITY}_{i,t}$ captures the level of algorithmic trading on stock 'i' on date 't', $\text{MCAP}_{i,t}$ denotes the logarithmic value of the market capitalization of stock 'i' on date 't'. $\text{INVERSE-PRICE}_{i,t}$ denotes the inverse of the price of the stock 'i' on date 't'. NIFTY-VOL_t denotes Nifty index volatiliity on day t.
Values in parentheses are t-statistics based on standard errors clustered at firm level.

	Event 1		**Event 2**	
	VWTD-OTR	VWTD-OTR INTENSITY	VWTD-OTR INTENSITY	VWTD-OTR
FEE DUMMY	-0.65	-0.38	0.11	48.35
	(-4.60)	(-5.28)	(0.71)	(4.99)
MCAP				
	0.77	0.62	0.51	24.68
	(1.60)	(2.73)	(0.81)	(0.69)
INVERSE-PRICE	111.56	47.69	115.48	15172.72
	(1.68)	(1.60)	(1.10)	(1.78)
NIFTY-VOL	-0.03	1.44	-24.81	-638.82
	(-0.04)	(2.66)	(-6.16)	(-3.43)
AT-INTENSITY	0.03	0.01	0.01	1.12
	(8.25)	(4.36)	(1.92)	(2.61)
Stock fixed effects	YES	YES	YES	YES
Adjusted R^2	0.11	0.11	0.01	0.06
Obs.	4,831	4,831	4,569	4,569

led to a drop in both OTR and the OTR intensity. The average OTR drops by a magnitude of 0.65 while OTR intensity drops by 0.39 after the imposition of the fee. Both these reductions are statistically significant at the 1 percent confidence level. Among the control variables, only AT intensity appears to be significantly impacting OTR. OTR and OTR intensity, which proxy for active management of limit orders, increase with increases in AT intensity. OTR intensity also see positive impact in times of high market volatility. These results suggest that the NSE was able to reduce the load on its infrastructure by reducing OTR (and the OTR intensity) through the introduction of the fee.

By 2013, NSE had significantly improved its infrastructure and was aggressively marketing its co-location services to algorithmic traders. This suggests that a high OTR was not likely of concern to the exchange that they would want to curtail. Thus, the impetus to increase the OTR fee to slow down AT may have come more from the regulator facing public criticism of adverse impact of algorithmic trading. Though the fee was raised substantially in 2013, it may have been less binding as key participants who are required to aggressively manage their orders, such as market makers, were exempt altogether, as were orders that were within 1 percent of the last traded price.[16]

We see that this is the case in Table 7. There is no change in OTR post-Event 2 while OTR intensity has gone up considerably after Event 2. This shows that the messaging intensity (over a relatively short period of time) has actually gone up contrary to what is expected following the increase of OTR fee. The overall model predictability has gone down, with lower adjusted R-square. Factors that were important in 2009 such as volatility and AT intensity appear to be not relevant (or less relevant) in explaining OTR and OTR intensity in 2013.

7.2.2 Impact of the fee on market quality

We now discuss the impact of Event 1 and Even 2 on market quality measures using DID regressions presented in Section 6.2.2. Table 8 shows the estimation results on liquidity measures for Event 1. An aggressive management of orders through OTR is expected to improve market quality. Quoted spreads and market impact costs are thus expected to be lower with higher OTR as is the Amihud's Illiquidity measure.

The introduction of OTR fee has led to higher spread and market impact costs after the introduction of the fee in 2009. The coefficient with the interaction term, TREATED×DUMMY is positive and significant for both the measures of transactions costs for Event 1. In comparison to the cash market, transactions costs on the futures market rose by 6 bps on average. Amihud's illiquidity measure is negative but insignificant, indicating no change in the (il)liquidity of the stock on the cash and the futures market after the event.

The overall depth[17] (DEPTH), and the TOP5DEPTH declined, with the coefficient on the interaction term being negative and significant. Based on the results for the transactions costs as well as the depth measures, we may

[16]Easley, de Prado, and O'Hara (2012) report that most HFTs are market makers and do not carry any inventory over the day. Therefore most of these high frequency traders would be exempt from any fee/penalty under a similar regime as that prevailing currently in the Indian markets.

[17]Logarithmic values of depth are used for the estimations.

Table 8 Regression results on liquidity measures for Event 1

The table presents the estimates on liquidity related market quality variables for Event 1. The the DID regression is specified below:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE-DUMMY}_t + \\ &\quad \beta_3 \times \text{TREATED}_i \times \text{FEE-DUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ &\quad \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ &\quad \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{MKT-QUALITY}_{i,t}$ is one of the market quality variable described in Section 5.2. TREATED_i is a dummy variable which takes value 1 for data related to the futures market, and 0 for the cash market. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{TREATED}_i \times \text{FEE-DUMMY}_t$ is the interaction term between the fee dummy and treated dummy. The remaining are control variables, as described in Section 6.2.1.
Values in parentheses represent the t-statistics, based on heteroskedsticity consistent robust standard errors.

	PRICE	QSPREAD	DEPTH	TOP1DEPTH	TOP5DEPTH	ILLIQ
FEE DUMMY	-0.004	0.001	0.126	0.037	0.096	0.301
	(-1.372)	(0.469)	(2.283)	(1.265)	(3.34)	(0.67)
TREATED	0.017	0.049	-0.223	0.921	0.811	0.185
	(2.39)	(7.529)	(-1.897)	(15.783)	(12.607)	(0.208)
TREATED×FEE DUMMY	0.067	0.057	-0.915	0.009	-0.094	-1.1
	(8.204)	(7.815)	(-10.721)	(0.236)	(-1.986)	(-1.456)
AT INTENSITY	-0.001	0	-0.003	0.006	0.002	-0.063
	(-1.69)	(-0.337)	(-0.684)	(2.828)	(1.03)	(-1.698)
MCAP	-0.032	-0.025	0.469	0.239	0.27	-3.183
	(-6.783)	(-5.317)	(10.248)	(7.195)	(8.364)	(-6.464)
INVERSE-PRICE	0.312	0.065	271.288	45.706	76.782	-273.458
	(0.232)	(0.058)	(10.585)	(3.071)	(4.342)	(-2.76)
NIFTY-VOL	0.345	0.286	-2.926	-0.818	-0.856	88.202
	(4.942)	(4.254)	(-8.914)	(-3.162)	(-3.264)	(8.169)
Adjusted R^2	0.18	0.24	0.66	0.58	0.53	0.15
Obs.	9,954	9,954	9,954	9,954	9,954	9,954

conclude that the fee introduction in 2009 adversely impact market making and liquidity provisioning by the traders.

Table 9 shows the estimation results on the volatility and the efficiency measures. The coefficient on the interaction terms, TREATED×DUMMY and VWTD-OTR×DUMMY turns out to be insignificant for the |VR-1| as well |BASIS| respectively, implying no effect of the fee on price efficiency. We however see a marked increase in the volatility measures: LIQRISK and σ_{BASIS}.

We now turn to analyzing Event 2, when the fee OTR fee was increased. Table 10 shows the DID regression estimates on the liquidity measures. In contrast to Event 1, the coefficient with the interaction term across all the measures is insignificant, indicating no impact on market quality. This holds true of the efficiency as well as the volatility measures as well, the results of which are presented in Table 9. We may conclude that none of the market quality variable was impacted as a result post Event 2.

Table 9 Regression results on efficiency and volatility measures for Event 1

The table presents the DID regression estimates on efficiency and volatility related market quality variables for Event 1. The regression is specified as:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} \quad = \quad & \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE-DUMMY}_t + \\ & \beta_3 \times \text{TREATED}_i \times \text{FEE-DUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ & \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ & \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{MKT-QUALITY}_{i,t}$ is one of the market quality variable (except the BASIS and basis risk, σ_{BASIS}), described in Section 5.2. TREATED_i is a dummy variable which takes value 1 for data related to the futures market, and 0 for the cash market. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{TREATED}_i \times \text{FEE-DUMMY}_t$ is the interaction term between the fee dummy and treated dummy. The remaining variables are control variables.
Fixed effects regression estimates specified by the following equation are reported for BASIS and BASIS RISK:

$$\begin{aligned}\text{INFO-EFFICIENCY}_{i,t} \quad = \quad & \alpha_i + \beta_1 \times \text{VWTD-OTR}_{i,t} + \beta_2 \times \text{FEE-DUMMY}_t + \\ & \beta_3 \times \text{VWTD-OTR}_{i,t} \times \text{FEEDUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ & \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ & \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{INFO-EFFICIENCY}_{i,t} \sim (\text{BASIS}, \sigma_{\text{BASIS}})$ for stock 'i' on date 't'. $\text{VWTD-OTR}_{i,t}$ denotes the value weighted average OTR on stock 'i' on date 't'. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{VWTD-OTR}_{i,t} * \text{FEE-DUMMY}_t$ is the interaction term between the value weighted average OTR and fee dummy.
Values in parentheses represent the t-statistics, based on heteroskedsticity consistent robust standard errors.

	|VR-1|	|BASIS|	RVOL	LIQRISK	σ_{BASIS}
FEE DUMMY	0.005	0.145	-12.931	-0.003	0.146
	(0.943)	(1.38)	(-13.978)	(-0.805)	(6.962)
VWTD-OTR		-0.044			-0.017
		(-3.00)			(-2.79)
TREATED	0.00		2.79	0.006	
	(0.074)		(1.871)	(0.736)	
TREATED×FEE DUMMY	0.00		-0.605	0.08	
	(-0.038)		(-0.494)	(11.968)	
VWTD-OTR×FEE DUMMY		0.101			0.065
		(4.222)			(5.911)
AT INTENSITY	0.00	-0.01	-0.039	0.00	-0.003
	(-0.728)	(-5.076)	(-0.941)	(-1.13)	(-4.052)
MCAP	-0.007	0.174	-4.778	-0.033	-0.013
	(-3.001)	(0.694)	(-7.699)	(-6.003)	(-0.216)
INVERSE-PRICE	-1.197	64.394	629.074	-2.371	8.79
	(-2.182)	(1.799)	(3.158)	(-2.021)	(0.481)
NIFTY-VOL	-0.171	3.361	162.475	0.36	2.489
	(-2.031)	(3.75)	(13.481)	(6.849)	(7.879)
Stock fixed effects	NO	YES	NO	NO	YES
Adjusted R^2	0.01	0.19	0.29	0.24	0.55
Obs.	9,954	4,831	9,954	9,954	4,831

Table 10 Regression results on liquidity measures for Event 2

The table presents the DID regression estimates on liquidity related market quality variables for Event 2. The regression is specified as:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE-DUMMY}_t + \\ &\quad \beta_3 \times \text{TREATED}_i \times \text{FEE-DUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ &\quad \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ &\quad \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{MKT-QUALITY}_{i,t}$ is one of the market quality variable described in Section 5.2. TREATED_i is a dummy variable which takes value 1 for data related to the futures market, and 0 for the cash market. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{TREATED}_i \times \text{FEE-DUMMY}_t$ is the interaction term between the fee dummy and treated dummy. The remaining variables are control variables.

Values in parentheses represent the t-statistics, based on heteroskedsticity consistent robust standard errors.

	PRICE	QSPREAD	DEPTH	TOP1DEPTH	TOP5DEPTH	ILLIQ
FEE DUMMY	0.002	0	-0.059	-0.057	-0.042	0.375
	(2.067)	(0.182)	(-2.572)	(-2.719)	(-1.883)	(1.82)
TREATED	-0.013	0.023	0.317	1.774	1.364	-1.091
	(-3.44)	(10.478)	(2.795)	(25.084)	(17.459)	(-2.386)
TREATED×DUMMY	-0.002	0	0.006	0.019	-0.031	-0.14
	(-1.335)	(0.041)	(0.142)	(0.649)	(-1.022)	(-0.543)
AT INTENSITY	0	0	-0.008	-0.006	-0.005	-0.008
	(0.687)	(-0.173)	(-2.968)	(-2.493)	(-2.135)	(-0.506)
MCAP	-0.015	-0.008	0.282	0.198	0.187	-1.478
	(-4.811)	(-4.804)	(4.352)	(4.405)	(3.724)	(-2.843)
INVERSE-PRICE	1.412	1.727	183.315	100.326	124.327	39.454
	(2.573)	(4.367)	(10.734)	(7.579)	(8.82)	(0.463)
NIFTY-VOL	-0.105	-0.062	3.602	2.98	2.806	61.322
	(-3.665)	(-3.636)	(6.158)	(5.534)	(5.308)	(5.25)
Adjusted R^2	0.37	0.57	0.59	0.82	0.75	0.11
Obs.	9154	9154	9154	9154	9154	9154

The result can be attributed to the design of the fee, which did not have any impact on the OTR itself (Table 7). The fee increase appears to be a non-event and more cosmetic than binding. AT intensity does not seem to impact market quality suggesting that the market quality is now more a function of the security's fundamentals such as size, market volatility and relative tick size than on the type of market participants involved.

Our results suggest that the OTR fell after Event 1 in 2009, worsening market quality. However, in 2013, when the fee was increased substantially in Event 2, there was neither a reduction of OTR nor a reduction in market quality since most orders with high OTR seem to have been exempted. For all practical purposes, Event 2 which was motivated by regulatory concerns, is a non-event.

Table 11 Regression results on efficiency and volatility measures for Event 2

The table presents the DID regression estimates on efficiency and volatility related market quality variables for Event 2. The regression is specified below:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} \quad = \quad & \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE-DUMMY}_t + \\ & \beta_3 \times \text{TREATED}_i \times \text{FEE-DUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ & \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ & \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{MKT-QUALITY}_{i,t}$ is one of the market quality variable (except the BASIS and basis risk, σ_{BASIS}), described in Section 5.2. TREATED_i is a dummy variable which takes value 1 for data related to the futures market, and 0 for the cash market. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{TREATED}_i \times \text{FEE-DUMMY}_t$ is the interaction term between the fee dummy and treated dummy. The remaining variables are control variables.
Fixed effects regression estimates specified by the following equation are reported for BASIS and BASIS RISK:

$$\begin{aligned}\text{INFO-EFFICIENCY}_{i,t} \quad = \quad & \alpha_i + \beta_1 \times \text{VWTD-OTR}_{i,t} + \beta_2 \times \text{FEE-DUMMY}_t + \\ & \beta_3 \times \text{VWTD-OTR}_{i,t} \times \text{FEEDUMMY}_t + \beta_4 \times \text{AT-INTENSITY}_{i,t} + \\ & \beta_5 \times \text{MCAP}_{i,t} + \beta_6 \times \text{INVERSE-PRICE}_{i,t} + \\ & \beta_7 \times \text{NIFTY-VOL}_t + \epsilon_{i,t}\end{aligned}$$

where $\text{INFO-EFFICIENCY}_{i,t} \sim (\text{BASIS}, \sigma_{\text{BASIS}})$ for stock 'i' on date 't'. $\text{VWTD-OTR}_{i,t}$ denotes the value weighted average OTR on stock 'i' on date 't'. FEE-DUMMY_t is the fee dummy which takes value 1 for post event dates, and 0 otherwise. $\text{VWTD-OTR}_{i,t} \times \text{FEEDUMMY}_t$ is the interaction term between the value weighted average OTR and fee dummy.
Values in parentheses represent the t-statistics, based on heteroskedsticity consistent robust standard errors.

	|VR-1|	|BASIS|	RVOL	LIQRISK	σ_{BASIS}
FEE DUMMY	0.009	0.111	1.172	0.00	0.009
	(2.63)	(1.15)	(2.478)	(1.105)	(0.729)
VWTD-OTR		-0.001			-0.002
		(-0.087)			(-1.48)
TREATED	-0.012		-0.921	-0.002	
	(-2.371)		(-0.875)	(-0.751)	
TREATED×FEE DUMMY	-0.012		-0.184	0.001	
	(-2.446)		(-0.279)	(0.679)	
VWTD-OTR×FEE DUMMY		0.003			-0.002
		(-0.021)			(-1.48)
AT INTENSITY	0.00	0.001	-0.017	0.00	-0.002
	(-1.386)	(0.554)	(-0.697)	(-0.584)	(-4.193)
MCAP	0.005	0.371	-4.274	-0.007	(-2.602)
	(2.089)	(1.407)	(-9.603)	(-3.732)	(-2.602)
INVERSE-PRICE	-0.442	22.682	632.09	-0.097	-0.561
	(-0.863)	(0.648)	(4.600)	(-0.300)	(-0.160)
NIFTY-VOL	-0.084	-12.604	53.45	-0.101	-0.407
	(-0.453)	(1.528)	(2.833)	(-5.442)	(-2.402)
Stock fixed effects	NO	YES	NO	NO	YES
Adjusted R^2	0.01	0.02	0.23	0.14	0.02
Obs.	9,154	4,569	9,154	9,154	4,569

7.3 The 1% LTP price limit in Event 2

In this section, we take a closer look at the implementation design of Event 2 to understand the insignificance of the event. As described in Section 4.1, the OTR fee implemented in 2012-13 was with certain exemptions. One of these exemptions was that orders with prices within the 1% last traded price (LTP) would be exempted from the fee. To know what percentage of orders fee outside this limit, for each stock, we compare the order price on each order event with the LTP in a day. Table 12 presents the results.

Table 12 Summary statistics of percentage of orders that breached the 1% LTP price limit

The table presents the mean and the median values of the percentage of order events on a stock that breached the 1% LTP price limit in a day.

	Pre	Post	p-value
Average	1.60	1.39	0.07
Median	1.07	1.02	0.24

The table shows that less than 2% of the orders were the ones that breached the 1% price limit even in the period prior the doubling of the fee. This reduced marginally from 1.60 to 1.39 after the fee implementation. This raises the question as to whether the regulator was targeting these 2% orders in the second stage fee implementation.

8 Conclusion

We provide one of the first studies to examine the impact of one of the popular regulatory interventions being proposed on HFT, which is a fee on the order-to-trade ratio. This fee was motivated by the need to check growth of HFT, both when it was first introduced and later when the fee was steeply raised. The fee was binding on all algorithmic traders when it was first introduced, but was largely limited in its scope due to exemptions when it was raised during the second intervention event.

Using proprietary data provided by the National Stock Exchange in India, we analyse market quality surrounding the two events. Overall, we find that while the first event in 2009 resulted in significant negative shifts in the market using several of the standard measures of market quality, the second event in 2012 resulted in almost no changes in market quality from before the intervention to after. While this might be a surprising finding at first, it is also worth underscoring that the second event which was actively championed by the regulator (unlike the first event) was also accompanied by several "get out of jail free" clauses in the regulation which resulted in traders simply adjusting their trading strategies to be on the right side of the regulation and not suffer the fee.

Our findings therefore question the underlying motivation, and the potential window dressing aspects of regulation that appear to protect markets from externalities imposed by some traders but provide enough exceptions that limit the effectiveness of such regulation. We show that well intentioned regulations may often be undermined in practice, leaving markets unaffected by the intervention.

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