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Keywords: Algorithmic trading; financial regulation; market efficiency; market liquidity; financial derivatives

JEL Code: G14, G18

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1 Introduction

The use of algorithms in securities markets, that enable order placement and trade execution at a rapid pace, has become the norm. It is argued that the ability to frequently modify orders reduces the fear of adverse selection for traders who provide free options to the market by submitting limit orders (Harris and Panchapagesan, 2005). Since technology aids the trader to manage adverse selection with greater certainty, high frequency trading using algorithms is expected to lead to better market liquidity. The speed advantage can also allow traders to react to news quickly and improves the informational efficiency of prices. These arguments find support in the empirical literature which finds that higher levels of algorithmic trading improves securities markets quality (Angel *et al.*, 2011; Hendershott *et al.*, 2011; Hasbrouck and Saar, 2013; Frino *et al.*, 2014; Boehmer *et al.*, 2012; Brogaard *et al.*, 2014).

But high levels of trading activity in financial markets has been viewed by policy makers and public opinion with scepticism. The growing dominance of high-frequency trading has often led to interventions to curb what is termed as 'excessive' trading activity. Sometimes the interventions are imposed by regulators, and sometimes by exchanges. The interventions have taken different forms, from technical barriers that slow down the rate of order placement into the trading systems to charges on order placement. An early example of such an intervention is the securities transactions tax (Tobin, 1978) which has been implemented at several exchanges across the world. A recently licensed U.S. exchange introduced a 350 micro-seconds delay (called a 'speed bump') on all orders in an effort to equalise access to the order book across all traders.[1] Research on the effect of several such interventions document an adverse effect on the target market. For example, when the Scandinavian countries imposed a transactions tax on equity trading in the 1980's, local trading activity and price discovery dropped and migrated to competitor markets in the Euro-zone (Umlauf, 1993). But despite such evidence, the search for an effective intervention to lower trading activity while retaining market quality continues.

In the recent times, a commonly used intervention to limit excessive trading activity is the *orders-to-trades ratio* (OTR) fee. This is a charge to a trader when her ratio of orders to trades crosses a fixed threshold. The Chicago Mercantile Exchange (CME) was the first implementation of this fee in 2005.[2] Since then, regulators globally have experimented with the fee. Studies from of exchanges such as Canada, Italy and Norway, that analyse the impact of the OTR fee, find that the impact varies across implementations, with more evidence that market liquidity deteriorates after an OTR fee than evidence that liquidity improves or that volatility decreases.[3]

In this paper, we argue that when an intervention is designed with the clearly stated

[1] The Investor's Exchange in the U.S., `https://iextrading.com`

[2] See `https://www.mypivots.com/board/topic/217/1/cme-cancellation-fees`.

[3] See Malinova *et al.* (2013); Friederich and Payne (2015); Jorgensen *et al.* (2018); Capelle-Blancard (2017).

objective to correct a market problem, it can be effective in achieving desired outcomes. We exploit a unique setting in the Indian equity market, where an OTR fee was used in two different instances but with different objectives. In the first instance, the OTR fee was imposed by the exchange during the early days of algorithmic trading in the country because the existing exchange infrastructure was limited and early adopters of algorithmic trading were able to dominate order placement into the limit order book. In the second instance, the securities market regulator used the OTR fee in response to public policy concerns about algorithmic trading.

In both instances, the fee was implemented *only* on derivatives trading unlike in other countries where the fee was implemented on trading in the spot. Further there was also a difference in the manner that the fee was implemented each time. In the first instance, the exchange applied the fee across all participants and all orders *uniformly*. In the second instance, the fee was applicable *only* on algorithmic orders that were placed *beyond* one percent of the last traded price. We use these features in a difference-in-differences framework to analyse the causal impact of the OTR fee.

The Indian equity markets offer an interesting setting where most of the trading is dominated on one exchange, the National Stock Exchange of India (NSE). We examine the single stock futures market at the NSE relative to the spot market. Unlike these markets elsewhere, the single stock futures (SSF) in India are highly liquid. This provides us an opportunity to explore how the dynamics between the underlying spot and the SSF market change when a fee is implemented on only one market.

In setting up the research design, we use the fact that the OTR fee was only applied to derivatives and not on the underlying spot markets. An obvious choice of the comparison group for the treated SSF is their underlying spot. However, we recognise that there is a potential endogeneity bias in these choices. The spot and the SSF are exposures on the same asset but with different trade-offs on leverage and liquidity. When costs of trading increases on one (in this case, the SSF), trading shifts to the other (the underlying spot) (Brunnermeier and Pedersen, 2009; Aggarwal and Thomas, 2019). In order to adjust for this endogeneity bias, we use a second microstructure feature in the Indian equity markets – that derivatives are not traded on all stocks. We use this to create a control group of stocks without derivatives that are *matched* to the stocks that have derivatives trading. We call the first set the *matched control* stocks and the second set are the *matched treated* stocks.

The difference-in-difference analysis of the *treated* SSF with the *matched control* spot captures the direct impact of the OTR fee. We also expect an indirect impact of the fee on the underlying spot market due to arbitrage linkages. We therefore, also conduct the analysis of the *matched treated spot* stocks with the *matched control spot* stocks to capture the indirect impact.

When the exchange implemented the fee, we find that the aggregate OTR level *reduced* for the *treated* SSF. At the same time, market liquidity of the treated SSF *improved* after the fee was imposed. Transactions costs *decreased*, depth *increased*, and both returns and liquidity volatility *reduced* for the treated SSF securities. These results are in contrast to previous studies that report a negative or no impact of the OTR fee on market quality.

In contrast, we do not find any impact of the fee when the regulator implemented the fee in the second instance. There is no significant change in the aggregate OTR level on the SSFs, and a limited impact on daily returns volatility. We do find a *reduction* in the percentage of orders placed beyond the one percent price limit. This suggests that market participants modified their trading behavior to mitigate the effect of the fee by submitting more orders where the fee was exempt, and less where it was not. This change in trading behavior, however, does not appear to effect market quality. These findings are in contrast to Jorgensen *et al.* (2018) who find that the fee reduced the OTRs in the Oslo stock exchange without any impact on market quality. They attribute the lack of any adverse impact on market quality to the design of the regulation which was tailored to encourage liquidity supply.

We take a closer look at the underlying mechanism that could be driving these results. If the intention of the OTR fee is to reduce 'unproductive orders and noise trading', then traders who are the source of such orders should have a different OTR level before and after it is implemented. Our data allows a closer look at the trading patterns of three different trader categories: institutional (INST), proprietary (PROP) and non institutional, non proprietary (NINP), of which the last is considered to be the 'retail' traders in the market. If retail traders are the most likely source of noise trading as suggested by Foucault *et al.* (2011), the OTR of this group is expected to change the most in response to the fee. A resultant decline in noise trading is likely to lead to a higher fraction of liquidity suppliers and informed traders in the market, which is likely to improve both market liquidity and efficiency. We find evidence that the OTR levels of the NINP category in SSF dropped significantly while that of the other categories remained unchanged when the exchange imposed the fee. This also likely drives why we find lower aggregate OTR levels *and* higher market quality after this fee was put in place. There are no such results of reduced aggregate OTR levels in the second implementation of the fee.

This leads us to argue that a clearly identified problem ought to motivate the design of an intervention. In first case when an OTR fee was put in place, the exchange identified unproductive orders which imposed negative externality on the overall market. The fee was applied without differentiating across participants, expecting that it would affect noise traders the most. The second fee implementation was motivated by public policy concerns that high frequency trading is likely to disrupt orderly trading, but without clarity on how the chosen design could reduce such trading.

Our paper contributes to the growing body of literature on how interventions on algorithmic trading effect trading behaviour and market outcomes. This is especially important because regulators worldwide often express concerns that call for interventions to curb algorithmic and high frequency trading. It also relates to the more general literature on market design issues and how increases in transactions costs affect trading outcomes.

The paper is organised as follows: Section 2 provides the context of how high frequency trading has continued to attract regulatory interventions despite mounting evidence that it improves market liquidity, and a discussion of applications of the OTR fee as a regulatory intervention to manage the effects of high frequency trading. This is followed by a discussion of the hypotheses we test in Section 2.1. Section 3 describes the microstructure of Indian equity market and details of different instances of OTR fee implementations in these markets. Section 4 describes the methodology and data used to measure the causal impact of the OTR fee. Section 5 discusses the results, and Section 6 concludes.

2 High frequency trading and regulatory interventions

Algorithmic trading (AT) and high frequency trading (HFT) have become the dominant method of trading in limit order book exchanges since the start of this century. The use of technology in financial market trading started from a regulatory directive to ensure that all customers are offered the best price at all times and across all markets. Empirical studies have amassed evidence that market quality has improved with a higher degree of AT and HFT (Hendershott *et al.*, 2011; Hasbrouck and Saar, 2013; Hendershott and Riordan, 2013; Menkveld, 2013; Brogaard *et al.*, 2014, 2015; Jarnecic and Snape, 2014). These show that there is an improvement in market liquidity as well as price efficiency when there is a change in systems that allow for low latency trading. Some of these present evidence from the U.S. markets, and some from markets in Europe.

These findings are consistent with the empirical evidence on the impact of AT on the Indian equity markets. Aggarwal and Thomas (2014) find that AT improves liquidity and reduces volatility. Bohemer and Shankar (2014) find that AT reduces the overall probability of systemic shocks in the Indian equity markets. Nawn and Banerjee (2018) find that proprietary algorithmic traders continue to supply liquidity even during periods of stress in the markets.

Despite the evidence, there remains substantial public discomfort and regulatory concerns about the effects of AT and HFT on markets. One source of the concern have been episodes when poorly constructed algorithms and ill-tested systems have occasionally been found to bring exchanges to a halt in the middle of a trading day. These have been viewed as systemic problems rather than episodic signs of market participants adjusting to AT and HFT. Some of these have become part of the everyday parlance including the 6^{th} May 2010 'Flash Crash' in the U.S. markets (Kirilenko *et al.*, 2017), the October 2014 United States treasury bond flash crash, the crash at Tokyo Stock Exchange triggered by excessive trading of *Livedoor* stock (Brook, 2005), and the crash at the NSE because of a fat-finger trade in the "Nifty" index futures in October 2012.[4]

[4]'Emkay admits error in Nifty crash; stock tanks 10%', *Mint*, October 2, 2012. Last accessed on March

Another concern is the possibility of higher incidence of market manipulation using AT and HFT. HFT is characterised by high order submission by AT which do not always convert into trades (Hagstromer and Norden, 2013). Such orders are seen as not constituting genuine liquidity and acts to counter some of the benefits of higher market liquidity that the academic literature attributes to AT and HFT. The empirical evidence on the incidence of market manipulation is sparse because such analysis requires information on trader-identifiers, which is rarely available. Few studies such as Egginton *et al.* (2016), Gai *et al.* (2012) and Van Ness *et al.* (2015) use indirect proxies and find evidence of higher quote stuffing activity in recent years. Manahov (2016) uses simulations and finds that HFT scalpers front-run the order flow, resulting in damage to market quality and long-term investors. This evidence along with the heightened fears of manipulative strategies such as layering, spoofing, and quote stuffing using HFT has prompted the regulators to find interventions to solve such forms of market abuse.

The interventions that are most widely implemented to slow down AT and HFT are of two types: those that use barriers in the trading mechanism and those that impose a penalty or fee on using AT and HFT. Some examples of the first include a *minimum resting time* for orders before any further action can be taken on them (such as the 350-microsecond 'speed bump' of the IEX) or a random delay between order arrival and order processing that seek to prevent a monopoly outcome among trading firms that chase cutting edge hardware systems in order to reach lowest latency (Harris, 2013). An example of the second type is the OTR fee which is charged on order placement or trade execution strategies that generate an orders to trade ratio above a given threshold value. Such a fee acts as a disincentive on placing frivolous or mischievous orders that other traders can act on. In the last few years, several exchanges have experimented with OTR fees to curb HFT including the CME, the Canadian Stock Exchange, the Italian Stock Exchange and the Oslo Stock Exchange.

The empirical evidence on the impact of the OTR fee is mixed. At the Italian Stock Exchange, Friederich and Payne (2015) find that the OTR fee led to a decline in aggregate market liquidity, while Capelle-Blancard (2017) find no significant impacts on market liquidity or volatility over a longer horizon. Malinova *et al.* (2013) find that a fee imposed on high number of messages in the Canadian markets impacted high-frequency market makers and resulted in an increase in transactions costs for various categories of investors in the market. Jorgensen *et al.* (2018) find that the fee did not cause any adverse changes to average liquidity at the Oslo stock exchange but did not find any benefits from the fee either.

Such mixed evidence naturally raises questions about the circumstances under which the fee achieves its intended consequences and when it fails to deliver. We capitalise on a unique opportunity when the OTR fee was implemented in the Indian equity derivatives market with different objectives across different instances. An OTR fee was first imposed by the exchange to better manage the high messaging load on its trading systems. At a later date, the fee was imposed by the regulator as a response to public policy pressure

18, 2019.

to regulate AT and HFT. In both cases, the fee was applied on the same market. But there were differences in the objectives of the intervention as well as in the design of the fee which we exploit to try and identify how a regulatory objective can effect the outcome of an intervention.

2.1 Hypotheses development

The main channel through which an OTR fee impacts market outcomes is by aligning the incentives of traders to refrain from sending 'unproductive' orders to the market or orders which may be the source of market manipulation. But the effectiveness of the fee in achieving its objective depends on whether it is binding and on what type of traders it is binding.

If the fee is binding, traders with high OTR will modify their trading activity as a response to higher transaction costs. This will lead to lower levels of aggregate OTR. If the fee is not binding, it will not have any impact on the OTR levels. For example, if the thresholds at which the fee is applicable are too high, or the fee itself is too low to deter any trading activity, then the fee is said to be not binding. Another scenario where the fee may not be binding is if it is imposed differently for different participants or differently on orders based on where they are placed in the limit order book. Traders can mitigate the effect of the fee by changing their trading behaviour to ensure that their orders fall outside of the zone where the fee is binding.

This reasoning leads us to posit the following hypothesis:

> **Hypothesis 1:** If the fee is binding and constrains traders who post orders which are not exempt, then the aggregate OTR level will *reduce*.

The OTR fee can also impact market quality. A large number of 'unproductive orders' puts a negative externality on other market participants by clogging the exchange bandwidth and increasing the overall latency in the market. This deters genuine traders from trading on the market and reduces the overall market liquidity. If the fee is effective in correcting such a practice, it can improve liquidity by increasing the fraction of genuine liquidity providers in the market. If genuine traders also comprise of informed traders, we expect a positive impact on the informational efficiency of prices as well. When an increase in transactions costs through an OTR fee adversely affects noise trading, we expect a reduction in returns volatility.

On the other hand, if the fee imposes higher costs on liquidity providers and informed traders, we expect a negative impact of the fee on market liquidity and price efficiency. The adverse impact of transactions taxes on market outcomes is well-studied (Matheson, 2011). Several previous papers analysing the impact of OTR fee also find a negative impact on market liquidity (Friederich and Payne, 2015; Malinova *et al.*, 2013). When an OTR fee is binding on liquidity providers and reduces their ability to update their orders in changing market conditions, the fee can adversely affect market liquidity. It can also bring down the informational efficiency of prices through a reduction in short term trading which reduces the profitability and trading activity of informed traders (Bloomfield *et al.*, 2009).

This reasoning indicates that the impact of an OTR fee on market quality could either be positive or negative, depending on which participants and orders are targeted, and on whether the fee is binding or not. This leads to the following two competing hypotheses:

> **Hypothesis 2A:** If the fee is effective in ensuring that only "unproductive" orders are deterred, liquidity and price efficiency improves after the fee is imposed.

> **Hypothesis 2B:** If the fee impacts liquidity providers and informed traders, liquidity and price efficiency reduces after the fee is imposed.

Finally, an OTR fee on one venue could cause trading to migrate to alternative, related venues where the fee is not charged. Colliard and Hoffmann (2017) argue that an increase in trading costs on one venue can lead to a change in trading composition itself. Participants sensitive to the fee will shift to a cheaper venue. The shift depends upon how similar the two venues are in their ability to contribute to price discovery and liquidity provision. If the two venues are indeed similar, then a fee that is binding on certain participants can result in migration of their trading from one venue to another. Alternatively, if the two venues are interlinked by arbitrage (such as the spot and the derivatives market), but the fee is only implemented on one venue, it could indirectly impact the alternative venue in the same direction[5] in terms of price efficiency and market liquidity.

Provided that the fee is binding, we posit the following hypotheses to test the indirect impact of the fee on alternative venue:

> **Hypothesis 3A:** If the two venues compete for liquidity, then an OTR fee imposed in one venue improves liquidity on the alternative venue.

> **Hypothesis 3B:** The fee indirectly impacts the alternative venue market liquidity and price efficiency in the *same* direction if the two markets are closely linked.

We examine the above hypotheses in the context of the OTR fee implementations on the Indian equity market. In the following section, we provide details of the structure of the fee along with the microstructure of the market.

3 Indian equity markets and OTR fee regimes

The market that we analyse is the National Stock Exchange of India (NSE) which is the dominant exchange for equity spot and derivatives trading in India. The NSE is one of

[5] As the other venue where the fee is implemented.

two national securities exchanges which predominantly trades equity securities[6] with a market share of 75% of the equity spot and about 98% of the equity derivatives market (SEBI, 2013). According to the data from the World Federation of Exchanges, NSE has consistently remained in the top five global exchanges that trade single stock futures (SSF) based on the number of contracts traded. In comparison, the single stock options volumes have started rising only in recent years,[7] contrary to the trends in the U.S equity markets where single stock options trading dominate equity derivatives trading activity.

In terms of microstructure, the NSE is similar to the leading global equity and equity derivatives exchanges. Trading takes places on an anonymous continuous electronic limit order book mechanism, where orders are matched on a price time priority.[8] There are around 1400 securities which are traded on the equity platform of NSE and 146 securities on which derivatives are traded, which include futures and options on single stocks and on indices. The selection of a derivatives security is based on the free float market capitalisation of the stock, average traded value and the price impact of a trade on the stock. The exchange is regulated by the Securities and Exchanges Board of India (SEBI). Both the selection criteria as well as the securities on which derivatives are strictly based on permissions from the regulator, SEBI.

AT was permitted by SEBI in equity and equity derivatives market in April 2008, but the levels of AT remained low until co-location was introduced in 2010. In 2009, the exchange detected that there was a high rate of order submissions on derivatives that rarely resulted in trades. In order to deter such orders and to reduce load on its infrastructure, the NSE levied a fee on high OTR on equity derivatives on October 1, 2009. The circular issued by the exchange stated the objectives of the fee as follows (NSE, 2009):

> "Of late, it is observed that the Order to Trade ratio in the F&O segment has been increasing significantly. Based on the analysis of the same, it has been observed that some trading members have been placing very large number of unproductive orders which rarely result into trades in the F&O segment which leads to increase in latency in order placement and execution for the other members. Such members are observed to have very large order to trade ratio which is significantly higher than the market average. In order to prevent such system abuse and to ensure fair usage of the system by all the members, it has been decided to levy a charge to deter system abuse in the F&O segment with effect form 1st October, 2009 as per the slabs below."

The fee was applicable only on equity derivatives and was computed at member level at the end of trading day. It was implemented uniformly across all market participants and

[6]The other securities exchange is the Bombay Stock Exchange, BSE.

[7]In India, most of the options volumes are concentrated on Nifty index options.

[8]Market trading hours are from 9:00 am to 3:30 pm. The opening price is determined through a pre-open call auction mechanism conducted between 9am to 9:15am. The closing price is a weighted average of the prices over the last half an hour of the trading day.

all order types, without any exceptions.[9] In June 2010, the exchange issued a circular which said that based on a 'notable' improvement in the OTR in the derivatives segment, it reduced the fee and raised the minimum thresholds for daily OTR.[10]

By 2012, the level of algorithmic trading on Indian markets increased to significant levels.[11] Concerned about the larger fraction of AT on Indian equity markets, the market regulator, SEBI, directed the exchanges to impose an OTR fee via a circular[12] in 2012 which stated:

> "In order to ensure maintenance of orderly trading in the market, stock exchange shall put in place effective economic disincentives with regard to high daily order-to-trade ratio of algo orders of the stock broker. Further, the stock exchange shall put in place monitoring systems to identify and initiate measures to impede any possible instances of order flooding by algos."

This intervention by SEBI was driven by public concerns regarding higher use of algorithms which could lead to order flooding by market participants. The fee in this episode was applicable *only* on algorithmic orders, and there were several exceptions within that. For example, all order entries that were placed or modified within one percent of the last traded price were exempt from the fee. Orders from designated market makers were also exempt.[13] The stated explanation for the exemptions was that the regulator wanted to minimise any adverse impact of the fee on the available liquidity at the best bid and ask prices in the limit order book. There was a further modification of the fees in May 2013, when SEBI directed exchanges to double the magnitude of the fee SEBI (2013). Table 1 summarises the details of the OTR fee implementation in both events.

Figure 1 presents a graph with vertical lines that mark the various dates of implementation of an OTR fee, superimposed on the fraction of the SSF trading volume at the NSE which was due to AT. In the graph, the solid vertical line represents the date on which co-location services commenced. The first vertical line is the date on which NSE imposed the OTR fee, the second line is when NSE reduced the fee, the third line is when SEBI imposed the fee and the last line is when SEBI raised the amount of the fee.

We focus our analysis on the first date, when the exchange imposed the OTR fee (NSE, 2009), and the third date, when the regulator imposed the OTR fee (SEBI, 2012; NSE, 2012). We select these two events because the design variations across these can help us to identify what makes the OTR fee effective.

[9]In implementation, this fee structure was similar to the OTR fee structure at the Italian Stock Exchange, Borsa Italiana in 2012 (Friederich and Payne, 2015).

[10]See NSE (2010).

[11]Aggarwal and Thomas (2014) shows that the level of AT increased from 20 percent in 2010 to 55-60 percent in 2013.

[12]See SEBI (2012)

[13]In India, designated market makers are only for the illiquid indices. The stocks covered in this study did not have any designated market maker under the *Liquidity Enhancement Scheme* (LES) under which exchanges were permitted to pay trading members a fee for maintaining two-way bids on select derivative contracts.

Table 1 Details of the instances of OTR fee implementation

2009-10	**2012-13**
• By the exchange on equity derivatives	• By the regulator on equity derivatives
• on all participants	• *not applicable* to participants who are market makers
• on all order types	• *only* on algo orders • *only* on orders *outside* ±1% LTP • with an additional penalty of a trading ban on the first 15 minutes on the next trading day if (OTR > 500). Imposed in 2013.

4 Data details and methodology

We use a difference-in-differences regression approach in order to identify the causal impact of OTR fee (hereafter, 'the fee') using the two events discussed in Section 3. Our analysis uses a three month period before and after the fee was imposed, for two distinct periods as follows:[14]

Event 1 when NSE imposed the fee on October 1, 2009

a) Pre event period: July 2009 to September 2009

b) Post event period: October 2009 to December 2009

Event 2 when SEBI imposed the fee on July 2, 2012

a) Pre event period: April 2012 to June 2012

b) Post event period: July 2012 to September 2012

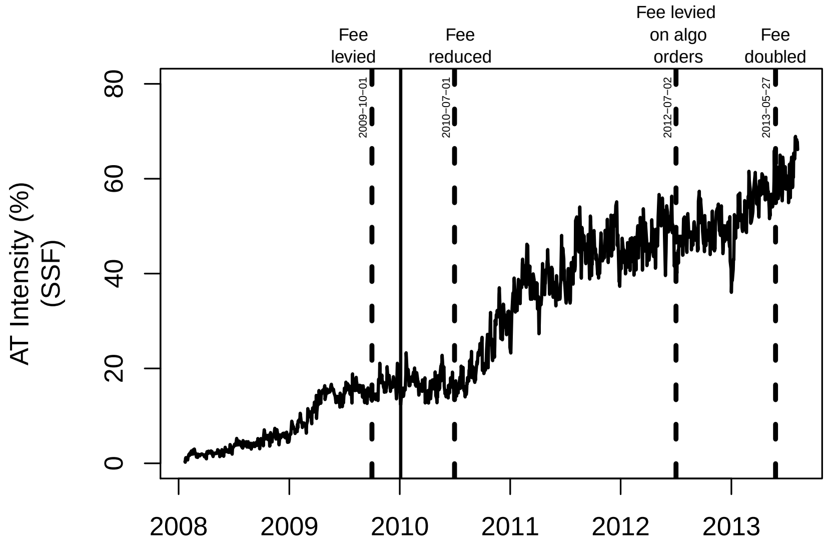
The data analysed is a proprietary tick-by-tick data-set of all orders and trades (TAO) in the equity and the SSF segment of NSE for the sample period. The data include details such as the type of order submitted, price and quantity, trader type ('institutional' (INST), 'proprietary' (PROP), 'non institutional nor proprietary' (NINP)),[15] whether the order/trade was sent by an AT or non AT, and the type of order event ('order entry', 'order modification', 'order cancellation'). Such data allows us to construct the full limit order book using which we compute OTR and various measures of market quality as described in the following section.

[14]We eliminate announcement effects by excluding the period between the date of announcement and implementation of the fee from our analysis. Event 1 was announced on September 7, 2009. Hence we remove the period from September 7, 2009 to October 1, 2009 from our analysis. Similarly, Event 2 was announced on June 29, 2012, and we remove the period from June 29, 2012 to July 2, 2012.

[15]The last category primarily comprises of retail traders.

Figure 1 AT intensity in single stock futures at the NSE

The graph shows the AT intensity on the SSF market at NSE between 2009 and 2013. AT intensity is measured as a fraction of the total traded value of AT trades in a day relative to the total traded value on that day. The solid vertical line indicates the date on which co-location was operationalised, January 2010. The first two dotted lines indicate dates of OTR fee intervention by NSE, and the last two dotted lines indicate the dates of OTR fee intervention by SEBI.



4.1 OTR and market quality measures

We test Hypothesis 1 using the *OTR* measure calculated at stock-day level. This is computed as the ratio of total number of messages received on a stock by the exchange to total number of trades on that stock. The number of messages is the sum of the number of order entries, modifications and cancellations in a day.

We test Hypotheses 2 and 3 using commonly used market quality measures of liquidity and price efficiency. Markets with lower transactions costs, and higher liquidity are viewed as higher quality markets. Similarly, markets with greater price efficiency, exhibit higher market quality (O'Hara and Ye, 2011). Our liquidity measures are based on *transactions costs* and *available depth* while the efficiency measures are based on *variance ratios* and *short term volatility.*

Transactions costs are measured in three ways which are (1) quoted half spread (QSPREAD), (2) impact cost (IC) and (3) Amihud's illiquidity (ILLIQ) measure. QSPREAD captures the cost for executing a small order by examining the percentage difference between the best bid and ask prices. IC is the measure of liquidity based on which the NSE filters stocks on which to trade derivatives. It measures the instantaneous cost of executing a certain quantity. Similar to effective spread, it is a pre-trade measure of transaction costs, and is computed as the difference between the execution price for a fixed transaction quantity and the mid-quote price divided by the mid-quote price at any given point of time. We calculate impact cost for three transaction sizes: Rs.250,000 (USD 3,800), Rs.500,000 (USD 7,600) and Rs.1,000,000 (USD 15,200).[16] The Amihud illiquidity measure (ILLIQ) is calculated ILLIQ as the ratio of absolute returns in a day to total traded value on that day (Amihud, 2002).

Four *depth* measures are calculated, which are (1) the Rupee value of orders available at the best prices in the limit order book (TOP1DEPTH), (2) the Rupee value of orders available across the best five prices (or TOP5DEPTH), (3) the Rupee value of orders available across the best seven prices (or TOP7DEPTH) and (4) the Rupee value of orders available across the best 10 prices (or TOP10DEPTH).

The *variance ratio* or VR (Lo and MacKinlay, 1988) is computed as the absolute value of the ratio of the variance of ten minutes log returns divided by two times the variance of five minutes log returns. A VR of one indicates a random walk. Under the null hypothesis of prices following a random walk, $|VR - 1|$ should be zero.

Short term price volatility is the *realised volatility* (σ_r) for each stock each day, which is calculated as the standard deviation of five minute returns. In addition, we also compute *volatility of liquidity* to measure liquidity risk. An argument often made against AT and HFT is that it is characterised by orders in the limit order book which are withdrawn before another trader can act upon it. Such behaviour in the market implies that we should expect high liquidity risk hurting the overall market quality. We use the standard deviation of the impact cost at various order sizes to capture the volatility of liquidity (LIQRISK).

Except for the ILLIQ measure, all the market quality measures are calculated using the full limit order book constructed out of the *TAO* data of the NSE. These limit order book based measures are first calculated for each stock at 1-second frequency, and then the median value for the day is used in the analysis. ILLIQ is calculated using daily data on returns and traded value.

4.2 Sample construction

The difference-in-differences (DiD) framework compares the stocks on which the fee is applicable (treated) to a set of comparable but untreated stocks (controls). The estimation differences out the effect of confounding factors which are common to both sets and isolates the impact of the fee. The SSF constitute the treated group since the fee in both the episodes was applied only on the derivatives traded on the exchange. One obvious choice

[16] These transaction sizes may appear small by global standards but the size of an average trade in the equity spot market was Rs.25,000 (USD 380), while the lot size in the derivatives market was Rs.250,000 (USD 3,800) during the period of our analysis. As of April 28, 2015, the lot size in the derivatives markets has been increased to Rs.500,000 or approximately USD 7800. This is beyond the period of the analysis and does not affect our results.

for the control group is the underlying stocks on the spot market where the fee did not apply. However, there are strong linkages between the SSF and the underlying spot. Higher costs on futures makes spot trading more attractive and can result in migration of trading to the spot market (Aggarwal and Thomas, 2019). The arbitrage link between the two markets can also result in the spot market getting adversely impacted by the fee. These indirect effects renders the underlying spot as a sub-optimal control group for the analysis.

We construct another comparison group so that the control group is not *directly* or *indirectly* affected by the fee. For this purpose, we exploit the fact that not all stocks listed on the equity platform of the NSE are traded on its derivatives platform. The NSE uses the following criteria to select stocks on which to trade derivatives:

1. The stock should be in the top 500 in terms of average daily market capitalisation **and** average daily traded value in the previous six months on a rolling basis.
2. The median 'quarter-sigma order size'[17] for the stock should not be less than an average of Rs.1 million over the last six months.
3. The market wide position limit (determined by the number of shares held by non-promoters) in the stock should not be less than Rs.3 billion.

We identify stocks that were close to, but did not fully satisfy, the above thresholds. These are stocks on which futures or options trading is not permitted. These 'non-SSF' stocks constitute our *comparison* group while stocks with SSF trading constitute the *treated* group on the spot market.[18] We then use propensity score matching to construct the sample for the treated and control groups. The propensity scores are estimated using a logistic regression using five covariates based on the exchange eligibility criteria for derivatives. The covariates are market capitalisation ("market cap"), prices, floating stock, turnover and number of trades.[19] The covariate values are calculated as the average for the period before the fee was announced. We use the nearest neighbor matching algorithm (without replacement) and a caliper of 0.05 to identify a one-to-one matching on estimated propensity scores for each treated stock. This ensures that the two groups are very similar to each other before the treatment.

Table 2 presents details of the initial sample and the sample selected after matching.[20] The matched sample has 39 treated and control stocks for Event 1, and 41 treated and control stocks for Event 2. Figure 2 presents the empirical distribution of the propensity score of the two groups, before and after matching. The overlap between the density of the two

[17]This is the trade quantity that can cause a price movement of quarter sigma.

[18]This approach brings us close to a regression discontinuity design (RDD). However, because the thresholds for market value and traded volume are not explicitly defined, we do not use the RDD framework.

[19]Using simulations, Davies and Kim (2009) show that one to one matching without replacement based on closing price and market capitalization is the most appropriated method to compare execution costs.

[20]We restrict the analysis to the top 500 stocks by market capitalisation. We also exclude stocks that underwent any corporate action including stock split, merger, rights and bonus issue or a buyback.

Table 2 Number of stocks used in matching stocks with SSF and stocks without SSF

The table shows the number of stocks in the sample for Event 1 when the fee was implemented by the exchange, and Event 2 when the fee was imposed by the regulator. 'Initial sample' indicates the number of stocks in the treated and control groups before matching. 'Final sample' indicates the number of stocks in each group after matching. 'Treated' contains the stocks with futures and 'Control' are the stocks without futures (non-SSF) on the NSE equity platform.

	Event 1		**Event 2**	
	Initial sample	Final sample	Initial sample	Final sample
Treated	156	39	187	41
Control	344	39	313	41

sets before matching indicates the region of common support. After matching, we can see that there is a tight overlap in the density curves of the final sample for each of the events. Table 3 reports the match balance statistics for each event and shows that there is a good match balance across all matching covariates between the treated and control firms in the final sample in the pre-intervention period.

Table 4 presents the pre-event mean and standard deviation of each market quality variable for the matched treated and control sample for Event 1 and 2 respectively. The statistics are presented for the SSF (treated-ssf), the stocks which are the underlying for the SSF in the spot market (treated-spot), and for the control stocks on the spot market (control-spot).

We see that the OTR levels for the SSF are higher compared to the underlying stocks (treated-spot). The OTR levels are comparable for treated and control stocks on the spot market, for both the events. The liquidity measures are somewhat better for the SSF compared to the treated and control group on the spot market, but the daily volatility (σ_r) is visibly different for the SSF compared with the spot market. We take these differences into account while constructing the difference-in-differences regression framework discussed in the next section.

4.3 Difference-in-differences (DiD) specification

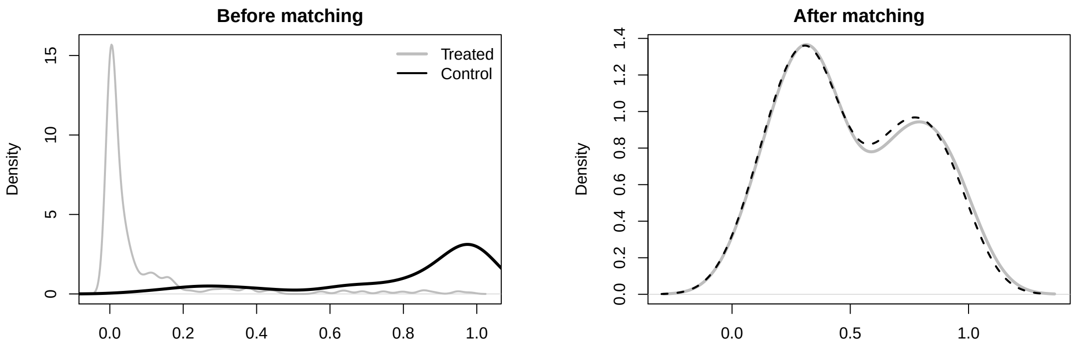
We use a difference-in-differences (DiD) regression framework to measure the impact of the fee and use the following model specification:

$$\begin{aligned} \textsc{measure}_{i,t} = \alpha + \beta_1 \times \textsc{treated}_i + \beta_2 \times \textsc{fee}_t + \beta_3 \times \textsc{treated}_i \times \textsc{fee}_t + \beta_4 \times \textsc{mcap}_{i,t} + \\ \beta_5 \times \textsc{inverse-price}_{i,t} + \beta_6 \times \textsc{nifty-vol}_t + \beta_7 \times \textsc{atintensity}_t \\ + \beta_8 \times \textsc{rollover-dummy}_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

Figure 2 Empirical distribution of the propensity scores before and after matching

The graphs show the density plot of the propensity score of the initial and final sample before and after matching for Events 1 and 2.

Event 1



Event 2

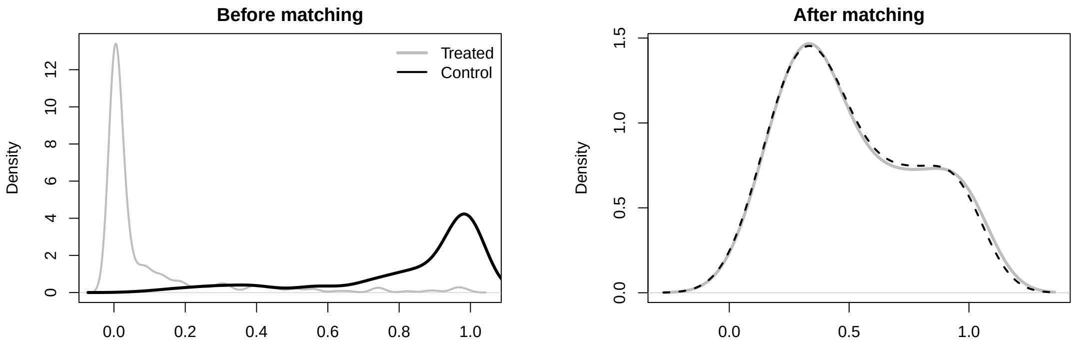


Table 3 Match balance statistics for Event 1 and Event 2

The table provides match balance statistics for the matched sample for both the events prior to the fee implementation. Panel A shows the matched balance statistics for Event 1 and Panel B shows the statistics for Event 2. μ_{tr} is the mean for the treated stocks, and μ_{cr} is the mean for the control stocks. The p-value is reported based on the t-test and Kolmogorov-Smirnov test for equality of mean and distribution, respectively.

	Before matching				After matching			
	μ_{tr}	μ_{cr}	p-value		μ_{tr}	μ_{cr}	p-value	
			t	KS			t	KS
Panel A: Event 1								
Distance (PS)	0.81	0.09	0.00	0.00	0.51	0.50	0.88	1.00
ln(MCap)	11.33	9.31	0.00	0.00	10.34	10.34	0.23	0.75
ln(Turnover)	5.88	2.79	0.00	0.00	4.87	4.88	0.44	0.56
Floating stock	49.17	45.20	0.04	0.14	51.33	44.88	0.11	0.15
ln(Price)	5.51	5.07	0.01	0.00	5.09	5.22	0.76	0.39
ln(# of trades)	9.76	7.24	0.00	0.00	9.08	9.06	0.96	0.75
Panel B: Event 2								
Distance (PS)	0.84	0.10	0.00	0.00	0.51	0.51	0.89	1.00
ln(MCap)	11.35	9.76	0.00	0.00	10.82	10.52	0.07	0.42
ln(Turnover)	5.30	2.09	0.00	0.00	4.15	4.16	0.29	0.99
Floating stock	47.94	40.32	0.00	0.00	45.86	43.00	0.56	0.92
ln(Price)	5.27	5.19	0.60	0.63	5.21	5.25	0.46	0.93
ln(# of trades)	9.52	6.70	0.00	0.00	8.57	8.56	0.41	0.59

where $\text{MEASURE}_{i,t}$ is one of the OTR or market quality measure described in Section 4.1 for stock 'i' on day 't'.

TREATED_i is a dummy variable which takes the value of one for a treated stock, zero otherwise. The estimated coefficient captures the pre-treatment mean differences in market quality variables across the two groups. FEE_t is a time dummy which takes the value of one for the period post the fee imposition, and zero otherwise, and it accounts for possible differences arising out of factors common to all stocks in the pre-event and post-event period. The interaction term coefficient, $\hat{\beta}_3$, measures the causal impact of the fee on $\text{MEASURE}_{i,t}$ and is what we will focus on for our analysis.

We also include control variables to account for stock-specific variation and changes in macroeconomic conditions. We use market cap ($\text{MCAP}_{i,t}$) and relative tick size measured by the inverse of the stock price ($\text{INVERSE-PRICE}_{i,t}$) to capture the stock specific variation. We control for the level of AT on each stock by including $\text{ATINTENSITY}_{i,t}$ which is measured as the percentage of AT traded volumes to total traded volumes on a stock in a day. Market volatility, measured as the realized volatility of intra-day returns on Nifty index (NIFTY-VOL_t) is used to capture the effect of macro-economic conditions. We also control for rollover effects of futures trading positions (from near month to next month expiry) using a ROLLOVER-DUMMY_t. The dummy takes the value one for the period two days prior to futures expiry and zero otherwise. All variables are winsorised at the 99% and 1% levels

Table 4 Summary statistics for treated and control stocks for Event 1 and 2

The table reports the pre-event mean and standard deviation (SD) of market quality variables discussed in Section 4.1 for the treated and control sample for Event 1 and 2. SSF (treated) shows the statistics for the treated sample for the futures market, while 'Treated spot' and (matched) 'Control spot' show the statistics for the treated and control spot market samples, respectively.

Market quality variable	**Treated SSF**		**Treated spot**		**Control spot**	
	Mean	SD	Mean	SD	Mean	SD
Panel A: Event 1						
OTR	25.82	8.35	1.30	0.35	1.10	0.32
QSPREAD (%)	0.19	0.07	0.06	0.02	0.08	0.05
IC_{250k} (%)	0.20	0.07	0.16	0.05	0.24	0.13
IC_{500k} (%)	0.24	0.09	0.21	0.07	0.30	0.14
IC_{1000k} (%)	0.33	0.13	0.27	0.09	0.33	0.15
ln(TOP1DEPTH)	13.42	12.30	12.15	11.83	11.79	12.02
ln(TOP5DEPTH)	15.32	14.53	14.22	13.88	13.83	13.95
ln(TOP7DEPTH)	15.68	14.79	14.57	14.19	14.21	14.25
ln(TOP10DEPTH)	16.08	15.10	14.95	14.53	14.62	14.56
ILLIQ	3.63	2.31	2.61	1.40	5.42	6.10
σ_r (%)	29.63	10.94	14.40	3.28	19.01	8.88
$\sigma_{\text{IC},250k}$ (%)	0.15	0.07	0.12	0.05	0.18	0.13
$\sigma_{\text{IC},500k}$ (%)	0.17	0.08	0.14	0.05	0.20	0.14
$\sigma_{\text{IC},1000k}$ (%)	0.21	0.10	0.14	0.08	0.16	0.09
|VR-1|	0.21	0.04	0.37	0.02	0.37	0.02
Panel B: Event 2						
OTR	69.36	54.59	6.29	7.41	5.10	3.19
QSPREAD	0.17	0.08	0.07	0.03	0.07	0.05
IC_{250k} (%)	0.19	0.09	0.20	0.10	0.24	0.10
IC_{500k} (%)	0.23	0.12	0.27	0.14	0.29	0.15
IC_{1000k} (%)	0.33	0.18	0.39	0.23	0.34	0.25
ILLIQ	3.81	3.21	4.74	3.83	5.86	4.25
ln(TOP1DEPTH)	13.36	12.90	11.86	11.88	11.98	12.85
ln(TOP5DEPTH)	15.23	14.79	14.06	14.16	14.07	14.78
ln(TOP7DEPTH)	15.62	15.22	14.50	14.66	14.44	15.08
ln(TOP10DEPTH)	16.03	15.63	14.94	15.14	14.80	15.37
σ_r	28.41	13.14	14.41	5.85	16.86	8.19
$\sigma_{\text{IC},250k}$ (%)	0.13	0.06	0.13	0.05	0.16	0.09
$\sigma_{\text{IC},500k}$ (%)	0.14	0.07	0.16	0.08	0.17	0.12
$\sigma_{\text{IC},1000k}$ (%)	0.18	0.09	0.21	0.17	0.11	0.06
|VR-1|	0.21	0.04	0.35	0.04	0.34	0.05

and the estimated coefficients are reported with standard errors that are clustered at the level of stock and day.

We test Hypotheses **1**, **2A** and **2B** by estimating Equation (1) using the SSF as the treated group and the *matched* non-SSF spot (control-spot) as the control group. The magnitude and the precision of the $\hat{\beta}_3$ coefficient provides evidence of the impact of the fee on OTR and market quality of the SSF. We test the indirect impact of the fee (Hypotheses **3A** and **3B**) by estimating Equation (1) with treated-spot as the treated group and the *matched* control spot stocks (control-spot) as the control group.

The DiD specification in Equation (1) relies on the common trends assumption which assumes that the outcome variables for both the treated and the control groups of stocks *co-move* closely in the absence of the fee. To test this assumption, we visually inspect the trends in our outcome variables prior the imposition of the fee for each event.[21] Figures A1 and A2 in the appendix present graphical evidence of this assumption on our measures of OTR and market quality. The trend in the values of these variables prior the imposition of the fee for both the events is similar for the treated and control group.

5 Results

In this section, we present the results of the difference-in-differences (DiD) regression described in Section 4.3. We first discuss the results for impact of the fee on the OTR level and then present the results for the impact on market quality.

5.1 Impact on OTR

Table 5 presents the estimation results of DiD specification in Equation (1) on the OTR level. Columns 2 and 3 present the results for Event 1 while Columns 4 and 5 present the results for Event 2.

We find a negative and significant $\hat{\beta}_3$ coefficient for Event 1. Compared to the matched control spot, the result shows that the OTR for the treated SSF declined by 3.45 units in magnitude (Column 2). In line with Hypothesis **1**, this indicates that the fee in Event 1 was binding on traders and managed to bring down the aggregate OTR level. Further, we also observe an indirect impact of the fee on the spot market for the treated stocks. The estimated value of the $\hat{\beta}_3$ coefficient in the treated spot - control spot DiD regression (Column 3) is positive and significant, showing that the mean OTR level for treated stocks on the spot market increased by 0.32 units relative to the matched control stocks. These results suggest that traders with high OTRs were sensitive to the fee, and migrated from SSF to the underlying spot as a consequence of the fee on the futures market.

[21] This is similar to the approach followed by Colliard and Hoffmann (2017).

Table 5 DiD estimates for the impact of the fee impact on aggregate OTR levels, Event 1 and Event 2

The table reports DiD regression results for the impact of the fee on OTR levels for both Event 1 and Event 2. 'Treated × Fee' is the interaction term that captures the estimated treatment effect ($\hat{\beta}_3$) of the fee on the level of OTR. The t-statistics based on standard errors clustered by stock and time are provided in parentheses. **Boldface** values indicate significance at 5% level.

	Event 1		**Event 2**	
	Treated(SSF)-Control(spot)	Treated(Spot)-Control(spot)	Treated(SSF)-Control(spot)	Treated(Spot)-Control(spot)
Fee	**-0.42**	0.04	**2.87**	**1.47**
	(-2.09)	(1.71)	(3.19)	(3.32)
Treated	**22.36**	**0.24**	**60.69**	1.31
	(15.11)	(3.88)	(8.69)	(0.85)
Treated×Fee	**-3.45**	**0.32**	7.41	4.42
	(-3.19)	(5.61)	(0.63)	(1.49)
Market cap	-0.39	0.04	0.19	0.74
	(-0.72)	(0.8)	(0.08)	(1.22)
Inverse Price	0.11	**-0.02**	-0.17	**-0.11**
	(1.67)	(-4.42)	(-1.78)	(-3.09)
Market Vol	-0.03	**0**	0.24	-0.02
	(-1.23)	(-2.47)	(1.86)	(-1.57)
AT intensity	**0.24**	**0**	0.09	-0.04
	(4.72)	(2)	(0.59)	(-1.27)
Rollover	**5.02**	0.01	0.73	0.61
	(4.05)	(0.33)	(0.63)	(1.89)
Excluded			-3.48	-6.36
			(-0.23)	(-1.63)
Adjusted R^2	0.65	0.34	0.26	0.13
# of obs	6060	6715	7485	9515

We next discuss the results for Event 2, when the regulator imposed the fee in 2012. In contrast to Event 1, we find that the coefficient with the interaction term for both the SSF and the spot is insignificant. This result implies that the fee in Event 2 did not have an impact on the aggregate OTR. We also observe that the magnitude of the $\hat{\beta}_3$ coefficient is large and positive for both the treated sets, indicating that the fee instead resulted in a higher aggregate OTR level after the event. This may have been undesirable given the initial objective of the regulator, which was to curb high OTRs in the market.

5.2 Impact on different trader categories

What could be the mechanism driving the results of both Event 1 and Event 2? The fee in Event 1 was implemented across all market participants on all orders. There was no way that the effect of the fee could have been mitigated by modifying the trading strategy on the SSF. Traders most sensitive to the fee will move their trading strategies involving high OTR to the market which did not have the fee.

We separately examine the impact of the fee on the OTR of each trader category: "INST", "PROP" and "NINP". This analysis helps us uncover which trader category was impacted the most by the fee. We estimate the DiD specification in Equation (1) for the OTR of each trader category separately. Table 6 shows the estimation results.

The results show that the fee had the largest impact on NINP traders. The OTR for the treated SSF declined by 4.15 units in comparison to matched control spot, while there is no significant impact on "INST" and "PROP" traders. This suggests that the reduction in aggregate OTR on the SSF market came through lower number of orders placed by the NINP traders after the fee implementation.

We also observe that the OTR level of NINP traders increased by 0.13 units for the treated spot relative to to the matched control (non-SSF) stocks. This suggests that the NINP traders moved high OTR strategies from the SSF to the spot. The OTR of "prop" traders also increased for the treated spot stocks in comparison to the matched control (non-SSF) spot after the fee was imposed (Column 7, Table 6). The analysis indicates that the fee on the SSF market resulted in lower order submissions (by the NINP category) on the SSF market, but higher order submissions by the NINP and "prop" category on the spot market.

During Event 2, the fee was implemented only on algorithmic orders placed beyond the 1% price limit of the last traded price (LTP). The impact of this design feature may have been the modification of trading strategies which ensured lower order placement where the fee was binding and a higher order placement where it was not applicable. We test this hypothesis by examining the percentage of orders placed beyond one percent (ORDERS-BEYOND) of LTP limit for our sample of treated and control stocks. The results are shown in Table 7.

Table 6 DiD estimates of the impact of the fee on each trader category, Event 1

The table reports the DiD estimation results for the impact of the fee on the OTR of each trader category: institutional (INST), proprietary (PROP) and non institutional non proprietary (NINP). 'Treated × Fee' is the interaction term that captures the causal effect of the fee on the OTR for the treated instruments. The *t*-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	Treated(SSF)-Control(Spot)			Treated(Spot)-Control(Spot)		
	OTR_{NINP}	OTR_{INST}	OTR_{PROP}	OTR_{NINP}	OTR_{INST}	OTR_{PROP}
Fee	-0.16	0.09	-0.68	**0.04**	0.03	0
	(-0.87)	(1.2)	(-1.37)	(1.98)	(0.68)	(0)
Treated	**16.35**	**3.97**	**39.26**	**0.21**	-0.07	0.08
	(13.1)	(9.65)	(12.5)	(3.34)	(-0.93)	(0.33)
Treated×Fee	**-4.15**	-0.67	-1.9	**0.13**	-0.07	**0.89**
	(-4.42)	(-1.68)	(-0.75)	(3.72)	(-1.26)	(4.89)
Market cap	-0.94	-0.2	-0.19	-0.01	-0.04	0.28
	(-1.67)	(-1.16)	(-0.1)	(-0.38)	(-1.42)	(1.24)
Inverse Price	0.14	0	0	**-0.01**	-0.01	**-0.06**
	(1.96)	(-0.12)	(0.01)	(-3.35)	(-1.89)	(-4.43)
Market Vol	-0.03	0.01	-0.02	**0**	0	**-0.01**
	(-1.36)	(0.79)	(-0.49)	(-3.64)	(-0.44)	(-2.79)
AT intensity	**0.14**	0.01	**0.37**	0	**0.01**	0.02
	(3.32)	(0.87)	(3.38)	(-0.61)	(3)	(1.96)
Rollover	**3.59**	0.55	**12.25**	0.01	0	-0.02
	(3.65)	(1.7)	(4.06)	(0.69)	(-0.15)	(-0.36)
Adjusted R^2	0.53	0.18	0.54	0.18	0.03	0.26
Treated	39	39	39	39	39	39
Control	39	39	39	39	39	39
# of obs	6060	5253	6060	6715	6194	6715

Table 7 DiD estimates for the impact of the fee on orders beyond 1%, Event 2

The table reports the DiD estimation results for the impact of the fee on the percentage of orders entered beyond 1 percent (ORDERS-BEYOND). 'Treated × Fee' is the interaction term that captures the causal effect of the fee on the OTR for the treated instruments. The *t*-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	Treated(SSF)-Control(Spot)	Treated(Spot)-Control(Spot)
	ORDERS-BEYOND	ORDERS-BEYOND
Fee	-2.67	**-3.47**
	(-1.81)	(-2.36)
Treated	-3.46	**11.42**
	(-1)	(3.68)
Treated×Fee	**-12.18**	**-7.01**
	(-4.09)	(-2.63)
Market Cap	0.18	0.69
	(0.15)	(0.61)
Inverse Price	**0.32**	**0.39**
	(3.81)	(3.81)
Market Vol	0.03	**-0.14**
	(0.34)	(-3.15)
AT Intensity	**-0.33**	**-0.38**
	(-5.93)	(-8)
Rollover	0.98	**1.65**
	(1.01)	(2.41)
Excluded	**11.77**	**9.36**
	(2.54)	(2.62)
Adjusted R^2	0.22	0.30
Treated	41	41
Control	41	41
# of obs	7485	9514

We find a significant *reduction* in the percentage of orders placed in the SSF limit order book beyond the one percent LTP limit relative to the spot. The reduction was 12% on an average. We also see a similar effect on the treated spot (Column 3) where the percentage of orders beyond the LTP limit reduced by 7%. These findings validate our hypothesis that the design variation in the implementation of the fee resulted in traders placing lower number of orders where it was binding, and an increase in order placement where it was not.

Did the impact in the aggregate OTR levels in Event 1 and 2 also have an effect on liquidity and price efficiency? Earlier studies suggest that a decline in the OTR is accompanied by a decline in the market liquidity as well (Friederich and Payne, 2015; Malinova *et al.*, 2013). But if the decline in the aggregate OTR level after Event 1 reduced the activity of traders who placed unproductive orders, then a lower OTR could have a positive impact on market liquidity. In the case of Event 2, a decline in the available limit orders beyond the one percent LTP limit can have adverse implications for the overall depth of the market. However, an increase in the percentage of orders within the one percent LTP limit may also reduce transactions cost for small trade sizes. We test for changes in both market liquidity and price efficiency in the following sections.

5.3 Impact on liquidity

Table 8 and 9 present the DiD regression estimation results for liquidity measures for Event 1 and 2 respectively. The measures include both transaction cost measures (QSPREAD, IC_{250k}, IC_{500k}, IC_{1000k}) as well as depth measures (TOP1DEPTH, TOP5DEPTH, TOP7DEPTH, TOP10DEPTH) and Amihud's ILLIQ measure.

We find that the treatment effect captured by the $\hat{\beta}_3$ coefficient is significant across all liquidity measures in Panel A for Event 1. The value of the coefficient with all the transactions cost measures (QSPREAD and IC for all transaction sizes) is negative and statistically significant. This implies that transactions costs of the treated SSF dropped relative to the control spot. QSPREAD dropped by 6 basis points and the impact cost measures dropped between 3 to 10 basis points at different transaction size levels. The estimates of the $\hat{\beta}_3$ coefficient for depth measures are also positive and significant, indicating improvement in depth in the range of 13 to 15 percent across different levels in the limit order book. This evidence of overall improvement in liquidity is further supported by the negative and significant coefficient for Amihud's illiquidity measure which indicates a reduction in the price impact of trades. The treatment effects do not show any adverse impact of the fee on market liquidity, and hence we do not find evidence in support of Hypothesis **2B**.

The results support Hypothesis **2A** that the decline in the levels of the SSF market OTR was accompanied by a simultaneous increase in market liquidity. This finding is contrary to the previous studies which find a negative impact of the fee when it is implemented universally across all participants and all orders (Friederich and Payne, 2015; Malinova

Table 8 DiD estimates for the impact of the fee on market liquidity, Event 1

This table reports Event 1 results of DiD regression on market liquidity variables in each column. The results are presented in two panels: Panel A presents the results for treated SSF and the matched control (non-SSF) spot while Panel B presents the results for treated spot and matched control (non-SSF) spot. The coefficient with the interaction term, 'Treated × Fee' ($\hat{\beta}_3$) captures the treatment effect. The *t*-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	QSpread	IC_{250k}	IC_{500k}	IC_{1000k}	top1depth	top5depth	top7depth	top10depth	illiq
Panel A: Treated (SSF) - Control (spot)									
Fee	0.01	-0.01	-0.02	0	0.03	0.04	0.05	0.04	-0.24
	(1.91)	(-1.94)	(-1.76)	(0)	(0.82)	(1.16)	(1.26)	(1.06)	(-0.58)
Treated	**0.13**	-0.02	-0.04	0.03	**1.9**	**1.69**	**1.68**	**1.66**	-1.22
	(9.48)	(-1.19)	(-1.79)	(1.05)	(19.11)	(18.83)	(18.77)	(18.81)	(-1.49)
Treated×Fee	**-0.06**	**-0.03**	**-0.05**	**-0.1**	**0.13**	**0.15**	**0.14**	**0.14**	**-1.18**
	(-6.8)	(-2.71)	(-3.41)	(-5.79)	(2.53)	(2.59)	(2.49)	(2.51)	(-2.08)
Market Cap	-0.01	-0.02	-0.02	**-0.03**	0.05	0.06	0.06	0.05	-0.54
	(-1.86)	(-1.77)	(-1.87)	(-2.19)	(1.12)	(1.25)	(1.16)	(1.02)	(-1.25)
Inverse Price	0	0	0	0	**0.02**	**0.03**	**0.03**	**0.03**	-0.04
	(-0.78)	(-1.22)	(-0.1)	(1.07)	(2.26)	(3.83)	(3.71)	(3.63)	(-0.93)
Market Vol	**0**	**0**	**0**	**0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**0.16**
	(9.35)	(13.52)	(13.23)	(9.82)	(-7.68)	(-10.06)	(-9.84)	(-9.97)	(7.73)
AT Intensity	0	0	0	0	0	0	0	0	0
	(-1.56)	(-1.63)	(-0.67)	(0.19)	(-0.61)	(-0.87)	(-0.95)	(-0.9)	(-0.16)
Rollover	**0.01**	0	-0.01	0	**0.12**	**0.13**	**0.13**	**0.13**	-0.17
	(2.38)	(-0.19)	(-0.89)	(0.03)	(5.13)	(4.99)	(4.67)	(4.3)	(-0.33)
Adjusted R^2	0.46	0.18	0.19	0.17	0.83	0.81	0.8	0.8	0.06
# of obs	6060	6058	6037	5740	6060	6060	6060	6060	6060
Panel B: Treated (spot) - Control(Spot)									
Fee	0	**-0.02**	-0.02	-0.01	-0.02	0.01	0.01	0.01	-0.3
	(-1.03)	(-2.22)	(-1.96)	(-0.55)	(-0.54)	(0.27)	(0.37)	(0.13)	(-0.74)
Treated	-0.01	**-0.07**	**-0.07**	**-0.04**	**0.38**	**0.39**	**0.35**	**0.31**	**-2.1**
	(-1.9)	(-3.51)	(-3.31)	(-2.06)	(4.36)	(4.66)	(4.16)	(3.63)	(-2.79)
Treated×Fee	0	0.01	0.01	-0.01	**0.19**	**0.18**	**0.19**	**0.21**	0.36
	(0.7)	(0.94)	(0.52)	(-0.62)	(3.9)	(3.5)	(3.52)	(3.71)	(0.74)
Market Cap	0	-0.02	**-0.02**	**-0.03**	**0.17**	**0.15**	**0.15**	0.15	-0.48
	(-0.65)	(-1.85)	(-2.05)	(-2.28)	(2.28)	(2.12)	(2.06)	(1.96)	(-1.27)
Inverse Price	0	0	0	**0**	**0.04**	**0.04**	**0.04**	**0.04**	-0.03
	(0.52)	(-0.25)	(0.72)	(2.14)	(5.36)	(7.27)	(7.33)	(7.4)	(-0.81)
Market Vol	**0**	**0**	**0**	**0**	**-0.01**	**-0.02**	**-0.02**	**-0.02**	**0.14**
	(9.56)	(12.86)	(13.01)	(9.5)	(-10.29)	(-10.05)	(-9.7)	(-9.81)	(7.29)
AT Intensity	**0**	**0**	0	0	**0.01**	**0.01**	**0.01**	**0.01**	-0.02
	(-3.46)	(-2.31)	(-1.78)	(-1.32)	(2.94)	(2.46)	(2.29)	(2.29)	(-1.11)
Rollover	0	**-0.01**	**-0.02**	**-0.02**	**0.09**	**0.09**	**0.09**	**0.09**	-0.44
	(-1.41)	(-6.39)	(-5.37)	(-3.69)	(6.26)	(5.16)	(4.72)	(4.19)	(-1.43)
Adjusted R^2	0.1	0.21	0.19	0.16	0.48	0.49	0.46	0.43	0.06
# of obs	6715	6713	6692	6379	6715	6715	6715	6715	6715

et al., 2013).[22]

A possible reason for the improvement in market liquidity on the SSF market could be due to a reduction in the number of unproductive orders. A high rate of unproductive orders increases latency for other market participants and reduces the incentive of liquidity suppliers to stay in the market. In Table 6 in the previous section, we saw that the source of the decline in aggregate OTR level was lower NINP trader category OTR. Since the NINP traders are most likely noise traders (Barber *et al.*, 2009; Foucault *et al.*, 2011), we argue that a reduction in order submissions by NINP traders lowers the fraction of unproductive orders in the market.

We also observed that the OTR values for the institutional and proprietary traders is negative but not significantly different from zero. These traders are recognized as liquidity suppliers (Aitken *et al.*, 2007). Hence we argue that the increase in SSF liquidity comes from the OTR reduction of the NINP (retail) traders, and higher trading activity by the other two categories.

We now discuss the indirect impact of the fee on the liquidity in the spot market. In Table 6, we found that the OTR for the NINP and proprietary trader category increased on the treated spot relative to the matched control spot. Did this increase improve the liquidity on spot market or worsen it?

Panel B in Table 8 shows no statistically significant impact on transactions costs of the treated spot stocks but there is a positive impact on the depth of these stocks across all levels. The depth increased between 18 to 21 relative to the matched control spot. Since the fee improved liquidity on both the SSF and the spot, we infer this as evidence in support of Hypothesis **3B** which states that the fee affects the alternative (spot) venue in the *same* direction as the SSF. We do not find evidence in favor Hypothesis **3A** where the alternative venue gains liquidity after an increase in the cost of trading SSF.

The channel for liquidity improvement in Event 1 may be attributed to the increased trading on the spot market by both NINP and proprietary traders. The other channel could be the positive improvement in the SSF liquidity which resulted in increased trading on the underlying spot. Overall, these results show that market liquidity *benefited* when the fee was imposed in Event 1, both directly as well as indirectly.

We next discuss the results for Event 2. Panel A in Table 9 shows the DiD regression estimation results for the impact on the SSF market. We find that the treatment effect for QSPREAD is statistically significant. The coefficient of interest, $\hat{\beta}_3$, is negative implying a reduction in the quoted half spread of treated SSF relative to the control spot. This improvement in liquidity is not seen in any other measure of transactions costs or depth. Hence, we conclude that there was no significant impact of the fee on the SSF liquidity after Event 2 and reject Hypothesis **2A** and **2B**. This result is not surprising because the

[22] A similar adverse impact of the French financial transaction tax was also found by Colliard and Hoffmann (2017).

Table 9 DiD estimates for the impact of the fee on market liquidity, Event 2

This table reports Event 2 results of DiD regression on market liquidity variables in each column. The results are presented in two panels: Panel A presents the results for treated SSF and the matched control (non-SSF) spot while Panel B presents the results for treated spot and matched control (non-SSF) spot. 'Treated × Fee' is the interaction term that captures the causal effect of the fee on the OTR for the treated sample. The t-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	QSpread	IC_{250k}	IC_{500k}	IC_{1000k}	TOP1DEPTH	TOP5DEPTH	TOP7DEPTH	TOP10DEPTH	ILLIQ
Panel A: Treated (SSF) - Control (Spot)									
Fee	**-0.01**	**-0.03**	**-0.04**	**-0.03**	0.09	0.1	**0.11**	**0.12**	**-0.96**
	(-2.81)	(-4.07)	(-3.82)	(-2.17)	(1.76)	(1.88)	(2.05)	(2.21)	(-2.66)
Treated	**0.11**	**-0.04**	**-0.05**	0.02	**2.12**	**1.8**	**1.76**	**1.75**	**-1.76**
	(8.7)	(-2.22)	(-2.01)	(0.69)	(16.78)	(14.23)	(13.79)	(13.82)	(-2.63)
Treated×Fee	**-0.04**	-0.01	-0.01	-0.06	0.09	0.14	0.12	0.1	0.09
	(-3.2)	(-0.46)	(-0.76)	(-1.92)	(1.04)	(1.4)	(1.25)	(1.05)	(0.16)
Market cap	-0.01	**-0.02**	**-0.02**	-0.02	**0.15**	**0.13**	**0.14**	**0.15**	**-0.68**
	(-1.55)	(-3.89)	(-3.2)	(-1.66)	(3.45)	(2.26)	(2.31)	(2.34)	(-3.14)
Inverse Price	**0**	**0**	**0**	**0.01**	**0.03**	**0.02**	**0.02**	**0.02**	0.07
	(7.94)	(2.79)	(2.59)	(2.8)	(4.57)	(3.98)	(3.67)	(3.42)	(1.91)
Market Vol	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0.03**
	(5.96)	(6.29)	(4.51)	(4.15)	(-3.92)	(-4.17)	(-3.8)	(-3.74)	(2.5)
AT intensity	**0**	**0**	**0**	**0**	0	0	0	0	-0.01
	(-3.94)	(-2.11)	(-2.17)	(-1.98)	(-0.84)	(-1.21)	(-1.2)	(-1.31)	(-1.15)
Rollover	0	-0.01	-0.01	-0.03	0	-0.02	-0.01	-0.02	-0.36
	(-1.82)	(-1.16)	(-1.58)	(-1.62)	(-0.06)	(-0.45)	(-0.24)	(-0.47)	(-0.94)
Excluded	**0.05**	0.04	**0.06**	**0.1**	-0.25	**-0.32**	-0.31	-0.27	1.23
	(3)	(1.77)	(2.03)	(2.27)	(-1.68)	(-2.01)	(-1.94)	(-1.74)	(1.34)
Adjusted R^2	0.56	0.32	0.3	0.34	0.76	0.67	0.65	0.65	0.11
# of obs.	7485	7482	7408	6442	7485	7485	7485	7485	7485
Panel B: Treated(SSF) - Control(Spot)									
Fee	**-0.01**	**-0.03**	**-0.03**	-0.02	0.08	0.1	**0.11**	**0.12**	**-0.96**
	(-2.6)	(-3.54)	(-3.29)	(-1.66)	(1.59)	(1.8)	(1.98)	(2.16)	(-2.64)
Treated	0	-0.01	0	**0.08**	**0.32**	**0.34**	**0.34**	**0.35**	-0.57
	(-0.17)	(-0.88)	(0.13)	(2.22)	(3.03)	(3.06)	(2.99)	(3.08)	(-0.83)
Treated×Fee	0	-0.02	-0.03	**-0.06**	**0.19**	0.18	0.19	0.19	-0.24
	(-1.29)	(-1.39)	(-1.87)	(-2.04)	(2.17)	(1.87)	(1.93)	(1.95)	(-0.5)
Market Cap	0	**-0.03**	**-0.03**	-0.03	**0.2**	**0.18**	**0.18**	**0.18**	**-0.79**
	(-1.62)	(-4.6)	(-4.14)	(-1.87)	(3.03)	(2.32)	(2.34)	(2.29)	(-3.82)
Inverse Price	**0**	**0**	**0**	**0.01**	**0.03**	**0.03**	**0.03**	**0.02**	**0.09**
	(16.01)	(3.39)	(3.15)	(3.06)	(5.98)	(5.02)	(4.66)	(4.32)	(2.71)
Market Vol	**0**	**0**	**0**	**0**	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**0.03**
	(9.07)	(8.12)	(5.64)	(2.9)	(-6.65)	(-5.68)	(-5.49)	(-5.4)	(2.07)
AT Intensity	**0**	0	0	0	0	0	0	0	-0.01
	(-2.47)	(-1.22)	(-1.31)	(-0.3)	(1.2)	(0.46)	(0.57)	(0.64)	(-1.08)
Rollover	**0**	0	-0.01	0.01	0.01	-0.02	-0.01	-0.01	**-0.45**
	(-1.98)	(-1.42)	(-1.41)	(0.22)	(0.68)	(-0.73)	(-0.44)	(-0.54)	(-1.98)
Excluded	0.01	**0.05**	**0.07**	**0.16**	**-0.37**	**-0.39**	**-0.42**	**-0.44**	**1.7**
	(1.83)	(2.87)	(2.68)	(2.25)	(-2.63)	(-2.5)	(-2.63)	(-2.78)	(2.17)
Adjusted R^2	0.67	0.34	0.33	0.12	0.45	0.35	0.33	0.31	0.13
# of obs.	9515	9512	9435	8304	9515	9515	9515	9515	9515

fee did not impact the aggregate OTR levels on the SSF market. We did find a decline in the percentage of orders sent beyond the one percent LTP limit. But we find that this change did not have any impact on the depth of the SSF market.

Panel B in Table 9 shows the indirect impact of Event 2 fee on the spot market. We observe that two liquidity measures have a significant $\hat{\beta}_3$ coefficient: impact cost at the largest transaction size (IC_{1000K}) and depth at best prices (TOP1DEPTH). $\hat{\beta}_3$ is negative for IC_{1000K} which shows that the treated spot had higher liquidity for large transaction sizes.

This result is puzzling because we saw a decline in the percentage of orders placed beyond the one percent LTP limit on the spot market in Table 7. The coefficient is positive for the TOP1DEPTH which shows that the treated spot experienced higher depth at the best bid and ask prices after the fee. This result could be attributed to the higher percentage of orders that were placed within the one percent LTP limit after the fee for the treated spot. The lack of significant impact on other liquidity measures leads us to conclude that there was limited impact of the fee in Event 2 on market liquidity.

In summary, the analysis of the impact of the fee on market liquidity suggests that liquidity in the markets benefited from using a fee on high rates of order submission, even though the strength of the results appear to be strong in the first event and weaker in the second. In the first event, the exchange was successful in using the fee to manage limited exchange infrastructure and improve market liquidity. The regulator had little success in using the fee to reduce the average OTR levels in the market but did appear to have an indirect positive consequence in terms of improved depth of the order book at best prices on the spot market.

5.4 Impact on efficiency

Table 10 and 11 present the DiD estimations of the effect of the fee on market efficiency measures described in Section 4.1. In both the tables, Panel A presents the results of the direct impact on the treated SSF while Panel B presents the results for the indirect impact on the treated spot stocks.

$\hat{\beta}_3$ is significant for all the efficiency measures in Panel A for Event 1. All four volatility measures are negative, showing decreased levels of returns volatility and liquidity risk for the treated SSF relative to the *matched* control spot. This reduction could be attributed to reduced NINP order submission on SSFs. However, we also find a positive and significant coefficient on the informational efficiency measure, $|VR - 1|$. This indicates that the fee adversely impacted informed traders who frequently need to update their orders in lieu of new information. The finding is in line with the result of Bloomfield *et al.* (2009) who find that a reduction in trading by uninformed traders, also reduces the trading activity of informed traders due to reduced profitability. This could cause price efficiency in the market to decline.

Table 10 DiD estimates for the impact of the fee on efficiency, Event 1

The table reports the Event 1 results of daily panel DiD on market efficiency variables in each column. Panel A presents the results for the treated SSF versus the control spot. Panel B presents the results for treated spot relative to matched control (non-SSF) spot. 'Treated × Fee' is the interaction term that captures the causal effect of the fee for the treated sample. The *t*-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	σ_r	$\sigma_{\text{IC},250k}$	$\sigma_{\text{IC},500k}$	$\sigma_{\text{IC},1000k}$	$\|VR-1\|$
Panel A: Treated (SSF) - Control (Spot)					
Fee	0.41	0	0	0.02	0
	(0.81)	(-0.44)	(0.44)	(1.66)	(-0.81)
Treated	**12.59**	-0.01	-0.02	**0.07**	**-0.16**
	(5.95)	(-0.36)	(-0.77)	(3.42)	(-19.84)
Treated×Fee	**-7.47**	**-0.05**	**-0.06**	**-0.11**	**0.01**
	(-5.73)	(-4.15)	(-4.55)	(-6.9)	(2.28)
Market Cap	-2.09	-0.01	-0.01	-0.01	0.01
	(-1.87)	(-1.45)	(-1.14)	(-1.34)	(1.14)
Inverse Price	-0.07	**0**	**0**	**0**	0
	(-0.72)	(-2.78)	(-2.97)	(-2.25)	(0.89)
Market Vol	**0.47**	**0**	**0**	**0**	**0**
	(12.75)	(8.7)	(8.15)	(8.68)	(-6.88)
AT Intensity	-0.09	0	0	0	0
	(-1.65)	(-0.25)	(0.4)	(-0.16)	(-0.01)
Rollover	1.1	**0.02**	0.02	**0.04**	0
	(1.66)	(2.04)	(1.44)	(2.61)	(-0.61)
Adjusted R^2	0.27	0.11	0.09	0.08	0.52
# of obs.	6060	6058	6034	5720	6060
Panel B: Treated (Spot)- Control (Spot)					
Fee	-0.76	0	0	0.01	0
	(-1.56)	(-0.66)	(0.31)	(1.36)	(0.48)
Treated	**-3.3**	-0.04	**-0.05**	0.01	0
	(-2.72)	(-1.9)	(-2.22)	(0.44)	(0.68)
Treated×Fee	0.45	-0.01	-0.01	0	0
	(0.75)	(-0.64)	(-0.74)	(0.05)	(-0.5)
Market Cap	-0.82	-0.01	-0.01	-0.01	0
	(-1.2)	(-1.38)	(-1.09)	(-0.94)	(1.87)
Inverse Price	-0.02	**0**	**0**	**0**	**0**
	(-0.26)	(-2.7)	(-3.56)	(-4.06)	(8.45)
Market Vol	**0.27**	**0**	**0**	**0**	**0**
	(15.07)	(8.32)	(8.07)	(8.83)	(-7.01)
AT Intensity	**-0.08**	0	0	**0**	0
	(-2.92)	(-1.14)	(-0.64)	(-2.01)	(-0.21)
Rollover	-0.42	**-0.01**	**-0.01**	0	0
	(-1.96)	(-2.9)	(-2.22)	(-0.44)	(1.65)
Adjusted R^2	0.16	0.1	0.09	0.04	0.1
# of obs	6715	6713	6689	6358	6715

In terms of Hypotheses **2A** and **2B**, the findings suggest a somewhat ambiguous impact of the fee on the efficiency measures. While the fee in Event 1 reduced the volatility in the market, it also reduced the informational efficiency of prices. We do not find any evidence of impact of the fee on the efficiency of the spot market (Panel B, Table 10). The coefficients with the interaction term for all efficiency measures are insignificant. Thus, the results do not support Hypotheses **3A** and **3B**.

We do not see a consistent change in $\hat{\beta}_3$ in Table 11 for Event 2. The coefficient with the interaction term is negative and significant, which implies a reduction in SSF returns volatility after the fee. The source of this decline is not clear since orders at the best prices were not impacted by the fee. We also observe a decline in the volatility of liquidity at the highest transaction size level ($\sigma_{\text{IC},1000k}$). This is consistent with the design of the fee, which was targeting order submissions beyond the one percent LTP limit. The results suggests a limited positive impact of the fee on price efficiency, which is in favor of Hypothesis 2A. We do not observe any indirect impact of the fee on spot market price efficiency, rejecting Hypotheses 3A and 3B.

6 Conclusion

Financial market regulators world wide increasingly mandate the use of charges and fees as a mechanism to manage the perception that there is excessive trading in securities markets. We exploit a unique opportunity in the Indian equity markets to study how effective such regulatory interventions are reducing this excessive trading, ideally by causing behavioural changes in order placement and trading strategies so as to explicitly improve market quality. We analyse two events of the OTR fee implementation. In one event, the exchange used the fee to manage infrastructure load. In the other the regulator imposed the fee in response to public policy concerns that high frequency / algorithmic trading was dominating outcomes on public securities markets.

This opportunity is unique because the two events play out in the same microstructure but are clearly separated in time. The securities are traded on platforms that are significantly more consolidated and highly liquid, unlike the fragmented markets seen in the U.S., so that the impact can be measured in a statistically robust manner. These market microstructure elements that allow us to frame the difference-in-difference regressions in a pair of innovative treated and control samples to strengthen the inference of the causal impact of the fee on the aggregate OTR levels, liquidity and efficiency of both the derivatives and the spot market. This is unlike previous studies where the fee is applied on trading in stocks on which trading is typically fragmented across exchanges, and it is more difficult to measure causal impact.

We find that when the exchange used the OTR fee to manage the pressure of high order submission rate on limited infrastructure, the aggregate OTR level reduced, the liquidity

Table 11 DiD estimates for impact on efficiency, Event 2

The table reports the Event 2 results of daily panel DiD on market efficiency variables in each column. Panel A presents the results for the treated SSF versus the control spot. Panel B presents the results for treated spot relative to matched control (non-SSF) spot. 'Treated × Fee' is the interaction term that captures the causal effect of the fee for the treated sample. The t-statistics based on standard errors clustered by stock and time are presented in parentheses. **Boldface** values indicate significance at 5% level.

	σ_r	$\sigma_{\text{IC},250k}$	$\sigma_{\text{IC},500k}$	$\sigma_{\text{IC},1000k}$	$\|VR-1\|$
Panel A: Treated (SSF) - Control (Spot)					
Fee	**-1.41**	**-0.03**	**-0.03**	0	0
	(-3.07)	(-3.21)	(-2.39)	(-0.18)	(-0.2)
Treated	**12.58**	-0.02	-0.03	**0.07**	**-0.13**
	(6.52)	(-1.28)	(-1.19)	(4.21)	(-17.69)
Treated×Fee	**-5.57**	0	-0.01	**-0.05**	0.01
	(-2.99)	(-0.07)	(-0.59)	(-2.96)	(1.36)
Market Cap	-1.15	-0.01	-0.01	0	**0.01**
	(-1.78)	(-1.33)	(-0.8)	(-0.24)	(3.2)
Inverse Price	**0.26**	0	0	**0**	**0**
	(7.11)	(1.18)	(1.25)	(2.49)	(9.77)
Market Vol	**0.09**	**0**	**0**	**0**	0
	(4.31)	(3.63)	(2.02)	(3.29)	(-0.22)
AT Intensity	**-0.09**	0	0	0	0
	(-3.49)	(-0.86)	(0.45)	(-1.42)	(1.52)
Rollover	-0.41	0.01	-0.01	0.01	-0.01
	(-0.92)	(1.34)	(-1.12)	(0.7)	(-1.36)
Excluded	**7.71**	**0.04**	**0.06**	**0.08**	-0.01
	(3.03)	(2.47)	(3.08)	(3.52)	(-0.94)
Adjusted R^2	0.45	0.08	0.03	0.13	0.38
# of obs	7485	7482	7388	6393	7485
Panel B: Treated (Spot) - Control (Spot)					
Fee	**-1.16**	**-0.02**	**-0.03**	0	0
	(-2.73)	(-2.98)	(-2.18)	(0.57)	(0.04)
Treated	-1.43	-0.02	-0.01	**0.09**	0
	(-1.78)	(-1.2)	(-0.61)	(3.26)	(0.98)
Treated×Fee	-0.65	0	-0.01	-0.05	0.01
	(-1.07)	(-0.44)	(-0.79)	(-1.83)	(1.72)
Market Cap	**-0.66**	-0.01	0	0	**0.01**
	(-2.13)	(-1.25)	(-0.81)	(-0.38)	(3.19)
Inverse Price	**0.29**	0	0	0	**0**
	(11.62)	(1.57)	(0.92)	(0.04)	(13.35)
Market Vol	**0.11**	**0**	**0**	**0**	0
	(7.69)	(5.72)	(2.9)	(3.03)	(-1.2)
AT Intensity	-0.02	0	0	0	**0**
	(-1.89)	(-0.37)	(0.39)	(-0.88)	(4.98)
Rollover	-0.33	0	0	0.01	**-0.01**
	(-1.55)	(0.5)	(-0.57)	(1.02)	(-2.96)
Excluded	**2.27**	**0.05**	**0.08**	0.08	**-0.02**
	(2.47)	(3.36)	(3.32)	(1.67)	(-2.96)
Adjusted R^2	0.58	0.09	0.03	0.04	0.21
# of obs	9515	9512	9415	8223	9515

improved and the volatility of returns and liquidity declined. When the regulator imposed the OTR fee only on orders that were *outside* of a 1% LTP limit, there was no impact on aggregate OTR and on most measures of market liquidity and efficiency. However, there was some improvement in the depth of the market at the best bid-and-ask as well as in the transactions costs at the touch. Unlike other studies in the literature, we do not find any evidence that the OTR fee significantly *worsened* market liquidity, in either instance when it was imposed in the market.

These results are a significant departure from the earlier literature that shows either a negative impact of such regulatory interventions on the overall market quality. Both these instances when the fee was imposed suggest that when the objective of the intervention shapes the exact form and design of the OTR fee, this can better shape the behavioural response of traders and, through this, resultant market quality.

The exchange had clearly identified that there were a few orders which were clogging up its bandwidth without improving market liquidity. The intervention was targeted at traders who were sending such orders and successfully managed to bring down their OTR levels, and thereby improve the overall market quality. The regulator imposed the fee in the form of guidelines on algorithmic trading but directed the exchanges to put in economic disincentives to curb high OTR from algorithmic traders. In the second intervention, there was no clearly visible evidence of the stated problem, other than the presence of high OTRs. There was effort to ensure that the fee would not impact the best bid-and-ask orders in the market, so as to minimise an adverse impact on the market quality.

The second implementation of the fee was similar to the Oslo stock exchange where also the liquidity supplying orders were exempted from the OTR fee. Jorgensen *et al.* (2018) do not find an adverse impact of the fee and conclude that differences in the design of the regulation drives the likely impact.

We argue that, in addition to the design, it is also essential to clearly identify the problem that the fee is seeking to correct in order to determine the likely impact and how effective it is. Clarity of the objective helps to define the expected benefit and the expected beneficiary of the intervention. This is important to consider because all market interventions have associated compliance costs for market participants who have to alter their behavior in response to such interventions. If the costs are higher than the benefits, then it may be socially and economically optimal not to impose the intervention.

In this paper, we present a cautionary tale of regulators intervening in market design: optimal outcomes are best guided with clear and focused objectives. Our analysis suggests that the regulators will be able to better deliver outcomes if the problem and the desired outcomes are stated upfront as part of the objective. Not only does it help to optimse the design of the market intervention, but also helps to lead to outcomes that can be readily measurable and visible to the public in whose interests the interventions are being done.

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A Parallel trends assumption

Figure A1 Pre-treatment outcome variables for matched treated and control stocks on the spot market around Event 1

The figure shows the evolution of outcome variables prior to the treatment for Event 1. For each variable, we plot the cross-sectional average for treated (black line) and control stocks (red line), minus the respective pre-event average. The graphs are shown for variables on the spot market for the treated set and the spot market for the matched control set.

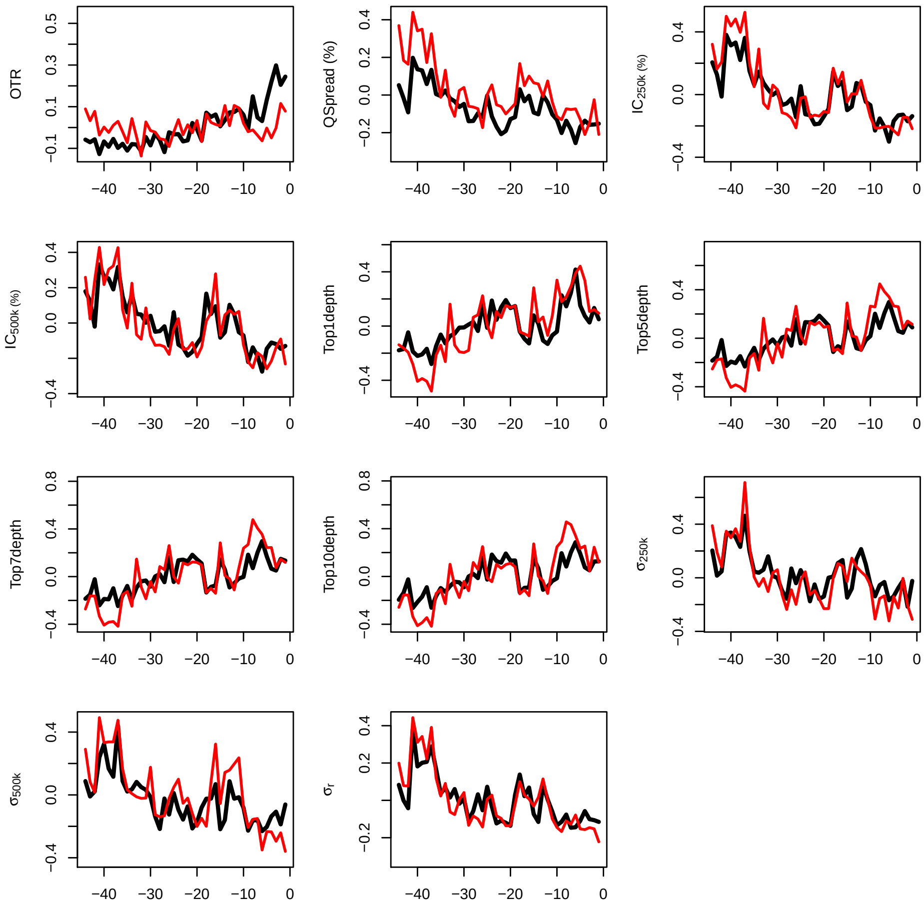

Figure A2 Pre-treatment outcome variables for matched treated and control stocks on the spot market around Event 2

The figure shows the evolution of outcome variables prior to the treatment for Event 2. For each variable, we plot the cross-sectional average for treated (black line) and control stocks (red line), minus the respective pre-event average. The graphs are shown for variables on the spot market for the treated set and the spot market for the matched control set.