When do regulatory interventions work?

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August 13, 2019

Abstract

Regulators worldwide have started to introduce measures like a fee on high order-to-trade ratio (OTR) to slow down high frequency trading. Previous studies on the OTR fee find mixed results about its impact on market quality. We study a natural experiment in the Indian stock market where such a fee was introduced twice with subtle variations in the implementation being driven by varying motivations. Using a difference-in-difference regression that exploits microstructure features, we find causal evidence of lower aggregate OTR and higher market quality when the fee was used to manage limited exchange infrastructure but little to no change in either OTR or market quality when it was used for a regulatory need to slow down high frequency trading.

JEL codes: G14, G18

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

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1 Introduction

The use of algorithms that enable order placement and trade execution in securities markets 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 those who submit limit orders and provide free options to the market (Harris and Panchapagesan, 2005). Since technology aids the trader to manage adverse selection with greater certainty, high frequency trading using algorithms can lead to better market liquidity. Such an ability also allows traders to react to news quickly and improves the informational efficiency of prices. These arguments are well-supported by empirical research 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).

However, high levels of trading activity induced by high frequency trading has also become a source of concern. In financial markets, policy makers and public opinion often view high trading activity as 'excessive noise', resulting in regulators and exchanges proposing or implementing some intervention to slow down such trading. These interventions take various forms. An early example is the securities transactions tax (Tobin, 1978), which several exchanges across the world have experimented with at different times. A recent example in the context of high frequency trading is the introduction of tiny delays (called a 'speed bump') that exchanges across the world are trying out in an effort to equalise access to the order book across all traders.[1] Empirical research has documented that such interventions have had 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). Colliard and Hoffmann (2017) find that the introduction of a financial transaction tax in France in 2012 did not result in any improvement in market quality. Instead, such a tax resulted in lower liquidity, and in turn, lower market quality. Similarly, the introduction of speed bumps at the TSX Alpha, a Canadian trading venue, suggests that market quality worsened post introduction, not just in TSX Alpha but also across other venues that did not introduce the speed bump (Chen *et al.*, 2017). Despite such evidence, the search for an effective intervention to lower trading activity continues.

In recent times, a commonly used intervention to limit excessive order activity has been 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 exchange to implement this fee in 2005.[2] Since then, more exchanges have used the OTR fee to slow down high frequency trading. These include the Italian Stock Exchange,

[1] The Investor's Exchange in the U.S., `https://iextrading.com` was the one of the first exchanges to implement a 350 micro-seconds time delay. More exchanges like Deutsche Borse, Intercontiental Exchange, London Metal Exchange are following the IEX in the US looking to introduce these speed-bumps to slow down high frequency traders. See "Futures exchanges eye shift to 'Flash Boys' speed bumps", Financial Times, May 30, 2019.

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

Toronto Stock Exchange, Oslo Stock Exchange, and National Stock Exchange of India. Research on the impact of the OTR fee at exchanges in Canada and Italy find that the fee resulted in a deterioration in market liquidity (Malinova *et al.*, 2018; Friederich and Payne, 2015; Capelle-Blancard, 2017). In contrast, KjellJørgensen *et al.* (2018) find that the same fee at the Oslo Stock Exchange managed to achieve lower OTR level, without any adverse impact on market quality. They attribute this finding to the specific design features of the fee, which exempted liquidity improving orders.

The differences in the results from these studies makes one ask: under what scenarios does an OTR fee achieve its objective? Is a universal fee on all market participants always bad? Does a fee with exemptions on liquidity providers achieve its objective of bringing down the aggregate OTR level without hurting market quality? In this paper, we examine these questions using two different episodes of the OTR fee implementation on the National Stock Exchange (NSE) of India. The objectives as well as the design of the fee across the two implementations were different. In the first implementation, the exchange introduced the fee to manage the high load on its limited infrastructure when a few early adopters of algorithmic trading dominated order placement into the limit order book. In the second event, the regulator implemented the OTR fee in response to public policy concerns about algorithmic trading. The design of the fee was different in each event: the first fee was applied *uniformly* on all participants and all orders while the second fee applied only on algorithmic orders that were placed *beyond* one percent of the last traded price and did not apply to market makers. These two episodes provide us a unique opportunity to understand how the nature of the intervention affects the outcomes.

We have access to detailed orders and trades data from the exchange, where each order is flagged as coming from an algorithmic trader or not. Each order is additionally tagged as being placed by one of three categories of trader: institutional, proprietary and non-institutional-non-proprietary. Of these, the third category are the 'retail' traders which are considered the most likely source of uninformed or 'noise' trading (Foucault *et al.*, 2011). These two features of the data allow us to analyse the impact of the intervention on trader behavior across different trader categories, and thus helps us to trace the source of the observed impacts on aggregate OTR level and market quality.

Several features about the market setting allow us to set up a research design that aids causal inference. Unlike other equity markets where trading is fragmented across multiple venues, the NSE has a 98 percent market share in equity derivatives trading in India, and a majority (more than 75 percent) share in equity spot trading. The single stock futures (SSF) market at the NSE is one of the most liquid in the world. The unfragmented order flow on a liquid platform implies that any migration that may occur as a result of the fee would be between the equity spot and derivatives market only, since migration to the other venue (the Bombay Stock Exchange) would come at a significant loss of liquidity.

In both episodes, the fee was implemented only on the equity derivatives segment of the exchange. This implies that the equity spot market, which did not come under the purview of the fee, could be used as the control group. However, the SSF and its underlying stock are exposures on the same asset with different leverage and liquidity trade-offs. When costs of trading increases on one venue, trading shifts to the other (Brunnermeier and Pedersen, 2009; Aggarwal and Thomas, 2019). This violates the basic assumption of non-interference of treatment with the control units which is necessary for causal inference. The substitution effect which may take place from the SSF to spot market will contaminate our inference on treatment effects (Boehmer *et al.*, 2019). To overcome this problem, we create a separate control group by exploiting a second feature of the Indian markets – not all stocks have derivative instruments traded on the exchange. To be eligible for derivatives trading, a security is required to meet well-defined minimum criteria. We use this criteria to identify our control group of stocks (without futures trading) which are *matched* to the (treated) stocks with futures trading.

We assess both the direct as well as the indirect impact of the fee in a differences-in-differences regression framework. The direct impact is measured by analysing the impact on the SSF market, obtained by comparing the *matched* treated stocks on the SSF market with the *matched* control stocks on the spot market. The indirect impact of the fee is measured by analysing the changes in the spot market for the underlying stocks, and is obtained by comparing the *matched* treated stocks on the spot market with the *matched* control stocks on the spot market.

Our results show that when the exchange first implemented the fee to disincentivise traders from putting excessive load on its system, it managed to achieve a lower aggregate OTR on the SSF market. We also find that this lower aggregate OTR was not achieved at the cost of lower liquidity, as documented in other studies (Friederich and Payne, 2015; Malinova *et al.*, 2018). In fact, we observe an improvement across all liquidity variables after the intervention for the treated stocks on the SSF market. These outcomes are supplemented by a reduction in returns volatility and liquidity risk. We argue that this improvement in market quality came from a reduction in "uninformed/noise" trading. A large number of unproductive orders on the exchange put a negative externality on other market participants by increasing the overall market latency on order placement. This may even crowd out liquidity providers from the market. When a fee manages to target the unproductive orders, it benefits the other market participants and thus helps improve market liquidity.

We examine this hypothesis by analysing the treatment effects across trader categories. We find that the OTR levels of the retail category, which is the most likely source of "uninformed/noise" trading (Barber *et al.*, 2009; Foucault *et al.*, 2011), decline significantly on the SSF market for the treated stocks after the fee intervention. The aggregate OTR levels of the other two categories of institutional and proprietary traders do not show any significant change. We attribute the observed higher liquidity on the SSF market after the fee implementation to the decline in the order activity of retail traders who are more likely to send unproductive orders than the other two categories of traders. Our results indicate that when the exchange clearly identified the market failure and the target audience that were to be impacted the most by the intervention, the fee had little to no negative consequence and instead had a positive effect.

In terms of the indirect effects on the spot market, we observe a substitution effect from the SSF market to the spot market. The aggregate OTR level on the spot market for the treated stocks increased after the intervention. When we decompose this increase across different trader categories, we see that most of this increase comes from the retail and proprietary trader categories. The findings suggest that traders switched high OTR related trading strategies from the venue where it was expensive to execute such strategies (SSF market) due to the fee, to the venue where it was not applicable (spot market). This substitution, though it increased the relative depth of the treated stocks, did not have any impact on the transactions costs and efficiency measures of the treated spot market.

In contrast, we find no impact of the intervention on the aggregate OTR level when the regulator implemented the fee on algorithmic traders out of public policy concerns. The fee in this episode came with certain exemptions, one of which was that orders within the one percent price limit of the last traded price would be exempt from this fee. A likely impact of this exemption was that traders modified their trading strategies to place their orders just within the one percent price limit threshold. This would manifest as reduced number of orders placed outside the threshold. Indeed, we observe a lower percentage of orders outside the threshold on both the SSF and spot market after the intervention. Here as well, we observe both a direct as well as indirect impact of the fee as changes in trading behavior to mitigate the effect of the fee. This change did not impact the liquidity of the SSF market, but did result in a decline in returns volatility and liquidity risk at higher transactions size level.

Our findings suggest that an intervention which is targeted at an identified market failure is more likely to achieve its intended outcome. There was little to no impact when the intervention was driven by regulatory concerns, much like what drives OTR fee interventions against algorithmic trading across the world. The microstucture setting of the Indian equity market used in identifying the treated and control groups avoids some of the endogeneity problems that can arise in similar settings and strengthens the causal inference of our results. Our paper additionally contributes to understanding how the design of the OTR fee can be successful in modifying traders' behavior. This adds to the growing body of literature about the effect of microstructure interventions on trading behaviour and, in turn, on market outcomes. This is especially relevant as regulators worldwide are increasingly seeking optimal interventions to curb algorithmic and high frequency trading.

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

Despite such evidence, there remains substantial public discomfort and regulatory concerns about the market impact of AT and HFT. Episodes of poorly constructed algorithms and ill-tested systems bringing exchanges to a halt in the middle of a trading day have contributed to these concerns. These include 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.[3]

Another concern is the possibility of higher incidence of market manipulation using AT and HFT. HFT is characterised by high order submission rates which do not always convert into trades (Hagstromer and Norden, 2013). Such orders are seen as not constituting genuine liquidity and act 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 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

[3] 'Emkay admits error in Nifty crash; stock tanks 10%', *Mint*, October 2, 2012. Last accessed on March 18, 2019.

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 submissions. Traders are penalised when the ratio of the number of order submissions to number of trades is above a certain 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 this kind of fee 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.* (2018) 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. KjellJørgensen *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 markets with different objectives at different instances, to try and identify how objectives can effect outcomes 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 and noisy' 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. If the fee is not binding, it will not have any impact on the OTR levels. An example of when the fee is not binding is if the thresholds at which the fee is applicable are too high, or the fee itself is too low to deter any trading activity. Another example 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. In such cases, traders can mitigate the effect of the fee by changing their trading behaviour so that their orders fall outside of the zone where the fee is binding. This reasoning posits the following hypothesis:

Hypothesis 1: If the fee is binding and constrains traders when posting orders, then the fee will lead to *lower* aggregate OTR levels.

A large number of 'unproductive orders' can place a negative externality on the market by clogging bandwidth and increasing the overall latency in the market. This deters genuine traders from participating and reduces the overall market liquidity. If the fee is effective in correcting the externality, it can improve liquidity by increasing the fraction of genuine liquidity providers in the market. If some of these are informed traders, we expect a positive impact on the informational efficiency of prices as well.

On the other hand, if the fee imposes higher costs on liquidity providers and informed traders, we can expect a negative impact on market liquidity and price efficiency.[4] Analysis of the impact of OTR fee have found adverse impacts on market liquidity (Malinova *et al.*, 2018). When the OTR fee is binding on liquidity providers, it reduces their ability to update their orders in changing market conditions. This can reduce market liquidity and lower the informational efficiency of prices through an adverse impact on the profitability of informed traders (Bloomfield *et al.*, 2009).

This suggests that the impact of an OTR fee on market quality could either be positive or negative, depending on whether the fee is binding or not, as well as on which participants and orders it is targeted. 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 will improve after the fee is imposed.

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

Finally, an OTR fee can change the patterns of trading on competing and complementary trading venues differently. Colliard and Hoffmann (2017) argue that an increase in trading costs on one venue can lead to participants shifting to a cheaper venue. If the two venues are similar, then a fee that is binding on certain participants can result in migration of their trading from one venue to another. If the two venues are interlinked by arbitrage (such as the spot and the derivatives market) but is only implemented on one venue, it could indirectly impact the price efficiency and market liquidity of the alternative venue in the same direction. Provided that the fee is binding, the following hypotheses can be tested:

Hypothesis 3A: If two venues compete for liquidity, then an OTR fee imposed in one venue leads to improved 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 linked by arbitrage.

[4]The adverse impact of transactions taxes on market quality is well documented (Matheson, 2011).

3 Indian equity markets and OTR fee regimes

We test the hypotheses posited in the previous section using data from the National Stock Exchange of India (NSE). The NSE is the dominant exchange for equity spot and derivatives trading in India[5] with a market share of 75% on the equity spot and about 98% on the equity derivatives market (SEBI, 2013). According to the data from the World Federation of Exchanges, it 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,[6] contrary to the trends in the U.S equity markets where single stock options trading dominate equity derivatives trading activity.

The market microstructure at the NSE is similar to the leading global equity and equity derivatives exchanges. Trading is done on an anonymous, continuous, electronic limit order book mechanism. Orders are matched with a price-time priority.[7] There are around 1800 stocks which are listed on the equity platform of NSE. Of that, derivatives instruments trade only on 166 stocks.[8] This includes futures and options on single stocks and on indices. Stocks are selected for derivatives trading 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 trading 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 if the OTR on equity derivatives trading crossed a stated threshold with effect from 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

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

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

[7] 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.

[8] As of May 2019.

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 (not just AT) and all order types, without any exceptions.[9] A year later, in June 2010, the exchange issued a circular where it reduced the fee and raised the minimum thresholds for daily OTR based on a 'notable' improvement in the OTR in the derivatives segment.[10]

By 2012, the level of AT on Indian markets increased to significant levels.[11] Concerned about the rising AT levels, the securities market regulator, SEBI, directed the exchanges to impose an OTR fee. The SEBI circular[12] in 2012 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."

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 across different episodes.

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.

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[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 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.

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.

4 Data details and methodology

We use a differences-in-differences regression in order to identify the causal impact of OTR fee using the two events discussed in Section 3. Our analysis uses a three month period before and after each selected event when the fee was imposed, 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

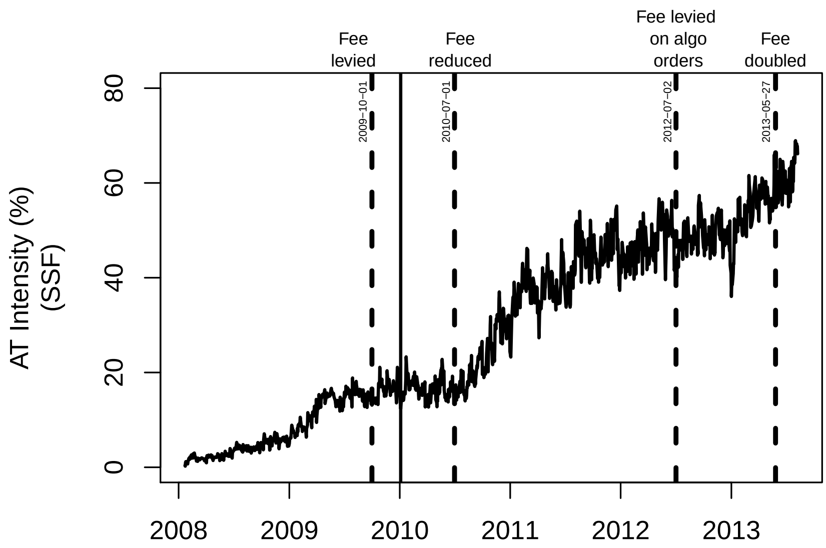
b) Post event period: July 2012 to September 2012

The data analysed is a proprietary data-set with all orders and trades (TAO) in the equity and the SSF segment of NSE for the sample period. In addition to the information on the buy / sell order type, price and quantity information, the richness of the data stems from additional details such as the type of order submitted ('order entry', 'order modification', 'order cancellation'), trader type ('institutional' (INST), 'proprietary' (PROP), 'non institutional nor proprietary' (NINP) and whether the order was sent by an AT or non-AT.

[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.

Figure 1 Fraction of algorithmic to total trades on single stock futures at the NSE

The graph shows the AT intensity on single stock futures at the NSE between 2009 and 2013. AT intensity is measured as a fraction of the value of algorithmic trades to the total value of all trades in a day. The trade is marked as AT if at least one side of the trade was generated by AT. The solid vertical line indicates the date on which co-location was considered to be operational at the NSE (January 2010). The first two dotted lines indicate dates of OTR fee intervention by NSE, and the last two dotted lines indicate dates of two OTR fee interventions by the regulator.



Such data allow us to construct the full limit order book at every order update, using to calculate the various measures described in the following section.

4.1 OTR and market quality measures

Hypothesis 1 requires 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.

Hypotheses 2 and 3 test the impact of the OTR fee on market quality, using commonly used market quality measures of liquidity and price efficiency. Liquidity measures are based on *transactions costs* and *available depth* while efficiency measures are based on *variance ratios* and *short term volatility*.

We measure *transactions costs* in three ways including (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 measures the instantaneous cost of executing a certain quantity and is the measure of liquidity which the NSE uses when selecting stocks on which to trade derivatives. 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).[15] The Amihud illiquidity measure (ILLIQ) is calculated 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. Under the null hypothesis of prices following a random walk, VR of one indicates a random walk and $|VR - 1|$ 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. 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 variance in liquidity hurting the overall market quality. We measure this liquidity risk (LIQRISK) using the standard deviation of the impact cost at various order sizes.

Except for the ILLIQ measure, all the market quality measures are calculated using the complete 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 differences-in-differences (DiD) framework compares the effect of the OTR fee on securities on which the fee is applicable (treated) to a set of comparable securities on which the fee does not apply (control). The estimation differences out the effect of confounding factors which are common to both sets and isolates the impact of the fee.

The SSF form the *treated group* since the OTR fee was only applied on these securities in

[15] 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.

India. One obvious choice for the *control group* is the underlying stock since the fee was not applied on these securities. However, there are arbitrage links between the SSF and the underlying stock. Higher costs on futures makes trading the underlying stock more attractive and can result in migration of trading to the equity stock market (Aggarwal and Thomas, 2019). This link between the two markets can result in the underlying stocks being impacted by the fee. This is an indirect effect which makes the underlying stock a sub-optimal control / contaminated control (Boehmer *et al.*, 2019).

We therefore construct an alternate control group using stocks which do not have derivatives trading. These stocks were unaffected by the fee either directly or indirectly. As the first step, we identify those stocks that are close to, but do not satisfy, the following criteria using which NSE selects equities 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'[16] 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.

This group of 'non-derivatives' stocks form the *control* sample while stocks with derivatives trading constitute the *treated* sample.[17] We next restrict the sample to only include the top 500 stocks by market capitalisation, and exclude stocks that underwent any corporate action including stock split, merger, rights and bonus issue or a buyback during the periods of our analysis. Lastly, we use propensity score matching approach where the scores are estimated using a logistic regression. The covariates used are based on the exchange eligibility criteria for derivatives, and include market capitalisation ("market cap"), prices, floating stock, turnover and number of trades.[18] 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, as can be seen in Table 2.

The final sample for Event 1 has 39 treated and and (matched) control stocks, while that for Event 2 has 41 treated and (matched) control stocks.[19] Figure 2 presents the empirical

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

[17]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.

[18]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.

[19]This is a marked reduction from the initial sample size. A larger sample for the treated and control groups could be achieved at a cost of a weaker match balance, which would contaminate the inference. Further, the top 100 stocks are the most traded stocks both on the equity and equity derivatives segment. The likelihood of finding a control group for these 100 stocks is therefore low.

Table 2 Pre- and post-matched samples for stocks with SSF (treated) and stocks without SSF (matched control)

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

distribution of the propensity score of the two groups, before and after matching. The overlap between the density of the two sets before matching indicates the region of common support. After matching, we find 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 for 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 selected samples for both OTR fee events. Treated SSF represents the set of matched treated stocks traded on the futures market that were directly affected by the fee. Treated spot represents the set of matched treated stocks traded on the spot market (the underlying market), on which the fee was not imposed. These stocks were likely to be indirectly affected as a result of the fee. Control spot represents the set of matched control stocks which are traded on the spot market. The OTR level for the Treated SSF is consistently higher compared to the OTR for both the Treated spot and the Control spot. There are no consistent patterns in the difference between liquidity of the Treated SSF compared to the Treated spot or the Control spot, but volatility is higher for the Treated SSF. We take these features into account while constructing the differences-in-differences regression framework discussed in the next section.

4.3 Differences-in-differences (DiD) specification

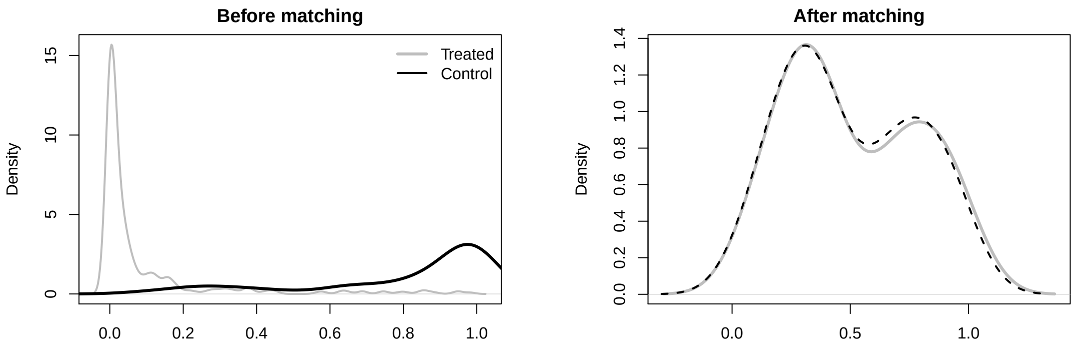
The following differences-in-differences (DiD) regression is used to measure the impact of the OTR fee:

$$\begin{aligned}\text{MEASURE}_{i,t} = \alpha &+ \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{FEE}_t + \beta_3 \times \text{TREATED}_i \times \text{FEE}_t + \beta_4 \times \text{MCAP}_{i,t} + \\ &\beta_5 \times \text{INVERSE-PRICE}_{i,t} + \beta_6 \times \text{NIFTY-VOL}_t + \beta_7 \times \text{ATINTENSITY}_t \\ &+ \beta_8 \times \text{ROLLOVER-DUMMY}_t + \epsilon_{i,t}\end{aligned} \tag{1}$$

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

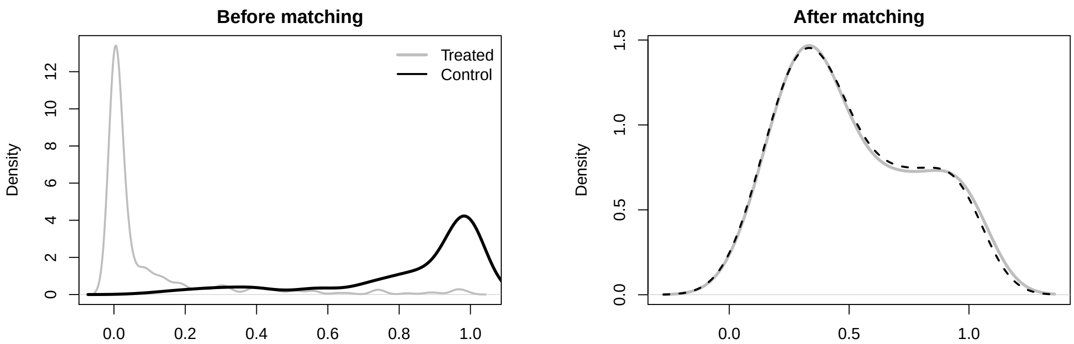


Table 3 Match balance statistics for Event 1 and Event 2

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 our coefficient of interest in 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 SSF, 'Treated spot' and (matched) 'Control spot' in the columns. The statistics for these variables during the first selected event when the NSE imposed the OTR fee is presented in Panel A, and statistics for the variables during the second selected event when SEBI imposed the OTR fee is presented in Panel B.

Market quality variable	**Treated SSF** Mean	SD	**Treated spot** Mean	SD	**Control spot** 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) for the Treated SSF compared to the Control spot. The magnitude and the precision of the $\hat{\beta}_3$ coefficient provides evidence of the impact of the OTR fee. We test the indirect impact of the fee (Hypotheses 3A and 3B) by estimating Equation (1) with the Treated spot compared to the Control spot.

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 samples *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, similar to the approach followed by Colliard and Hoffmann (2017). 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 before the fee is imposed is similar for the treated and control groups in both events.

5 Results

We present the results of the differences-in-differences (DiD) regression described in the previous section. 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 that the aggregate OTR levels dropped after the fee for Event 1. Relative to the control stocks (Control spot), the OTR level of treated stocks on the SSF market (Treated SSF) reduced by 3.45 on average after Event 1. This finding is consistent with Hypothesis 1 which says that if the fee was binding on traders, it would reduce the aggregate OTR level. The regression estimate of $\hat{\beta}_3$ for the treated stocks on the spot market (Treated spot) turns out to be positive and significant, indicating a 0.32 units increase in the OTR level for these stocks relative to control stocks on the spot market. This finding indicates that some amount of trading involving high OTRs migrated to the spot market after the fee imposition on the SSF market. Thus, there was indeed an indirect impact of the fee on the spot market for the treated stocks.

In contrast to Event 1, we do not find any significant impact of the fee on the average OTR level after Event 2. The estimated coefficient on the interaction term for both sets of treated stocks (SSF as well as spot) is insignificant. This result implies that the fee in Event 2 did not have an impact on the aggregate OTR, neither directly nor indirectly. In

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. ** denotes statistical 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	-0.422**	0.037	2.875**	1.471**
	(-2.087)	(1.711)	(3.188)	(3.315)
Treated	22.362**	0.236**	60.69**	1.307
	(15.115)	(3.878)	(8.685)	(0.854)
Treated × Fee	-3.453**	0.325**	7.41	4.419
	(-3.191)	(5.613)	(0.631)	(1.487)
Market cap	-0.387	0.042	0.19	0.74
	(-0.724)	(0.799)	(0.084)	(1.224)
Inverse Price	0.109	-0.022**	-0.173	-0.113**
	(1.665)	(-4.42)	(-1.78)	(-3.093)
Market Vol	-0.027	-0.002**	0.238	-0.019
	(-1.225)	(-2.469)	(1.859)	(-1.574)
AT intensity	0.239**	0.005**	0.092	-0.039
	(4.721)	(2.003)	(0.59)	(-1.271)
Rollover	5.015**	0.007	0.738	0.607
	(4.051)	(0.332)	(0.634)	(1.892)
Excluded			-3.475	-6.358
			(-0.231)	(-1.628)
Adjusted R^2	0.65	0.34	0.26	0.13
# of obs	6060	6715	7485	9515

fact, though statistically insignificant, $\hat{\beta}_3$ is large and positive indicating an increased level of aggregate OTR after the fee was imposed in Event 2.

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, giving traders little flexibility on modifying their strategies to avoid the fee other than to shift some trading to the alternate venue which did not have the fee. We hypothesise that a binding OTR fee would be most costly on uninformed traders. In order to test this hypothesis, we examine the effect of the fee on the aggregate OTR level across different trader categories: institutional (INST), proprietary (PROP) and retail (NINP) traders. As widely discussed in the literature (e.g, Foucault *et al.* (2011), Barber *et al.* (2009)), the third category, retail (NINP), is the largely the main contributor in uninformed / noise trading. We thus expect that the aggregate OTR level of the NINP category was affected the most after the fee. We test this hypothesis by estimating the DiD specification in Equation (1) for each trader category. Table 6 presents the estimation results.

The results show that the fee had the largest impact on retail (NINP) traders for whom $\hat{\beta}_3$ is -4.15 and significant for the Treated SSF relative to the Control Spot, while there is no significant impact seen in the estimated coefficients for the institutional or proprietary traders. This suggests that the reduction in aggregate OTR on the SSF market came through lower number of orders submissions by retail traders after Event 1.

We also observe that $\hat{\beta}_3$ is positive and statistically significant for the Treated spot relative to the Control spot for the retail category. This suggests that retail traders moved some of their trading activity from the SSF to the underlying stocks, which did not have the fee. The aggregate OTR of proprietary traders also increased for the Treated spot after the fee was imposed (Column 7, Table 6). The analysis indicates that the OTR fee on SSF resulted in lower order submissions by the retail traders on SSF, and higher order submissions by retail and proprietary traders on the Treated spot stocks. These two together contribute to the reduction in the aggregate OTR level on the SSF market, and an increased OTR level on the spot market for the treated stocks.

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 is likely to be 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 presented in Table 7.

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 Control spot. The reduction was 12% on average. We also see a similar effect on the Treated spot (Column 3) where the

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 institutional (INST), proprietary (PROP) and retail (NINP) traders. '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. ** denotes statistical 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	-0.157	0.091	-0.683	0.038**	0.028	0
	(-0.866)	(1.198)	(-1.37)	(1.983)	(0.68)	(0)
Treated	16.355**	3.972**	39.261**	0.208**	-0.07	0.08
	(13.095)	(9.649)	(12.503)	(3.342)	(-0.93)	(0.327)
Treated×Fee	-4.149**	-0.673	-1.904	0.131**	-0.066	0.894**
	(-4.423)	(-1.677)	(-0.746)	(3.725)	(-1.265)	(4.888)
Market cap	-0.937	-0.198	-0.193	-0.01	-0.043	0.278
	(-1.669)	(-1.156)	(-0.104)	(-0.382)	(-1.422)	(1.235)
Inverse Price	0.143**	-0.002	0.002	-0.012**	-0.008	-0.06**
	(1.963)	(-0.117)	(0.012)	(-3.346)	(-1.891)	(-4.434)
Market Vol	-0.029	0.006	-0.025	-0.003**	-0.001	-0.009**
	(-1.361)	(0.793)	(-0.491)	(-3.641)	(-0.439)	(-2.789)
AT intensity	0.144**	0.014	0.374**	-0.001	0.012**	0.024**
	(3.318)	(0.873)	(3.384)	(-0.614)	(2.998)	(1.962)
Rollover	3.588**	0.553	12.247**	0.014	-0.005	-0.017
	(3.651)	(1.698)	(4.057)	(0.691)	(-0.155)	(-0.364)
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. ** values indicate statistical significance at 5% level.

	Treated(SSF)-Control(Spot)	Treated(Spot)-Control(Spot)
	ORDERS-BEYOND	ORDERS-BEYOND
Fee	-2.669	-3.471**
	(-1.805)	(-2.359)
Treated	-3.462	11.425**
	(-1.004)	(3.677)
Treated×Fee	-12.182**	-7.012**
	(-4.09)	(-2.63)
Market Cap	0.175	0.691
	(0.153)	(0.607)
Inverse Price	0.324**	0.391**
	(3.806)	(3.81)
Market Vol	0.026	-0.139**
	(0.338)	(-3.154)
AT Intensity	-0.333**	-0.385**
	(-5.929)	(-8.003)
Rollover	0.981	1.648**
	(1.01)	(2.415)
Excluded	11.768**	9.359**
	(2.536)	(2.617)
Adjusted R^2	0.22	0.30
Treated	41	41
Control	41	41
# of obs	7485	9514

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.

In summary, our findings indicate that the fee after Event 1 managed to achieve the intended consequence of a reduction in high OTR level. This reduction came from a reduced level of aggregate OTR of the retail category which is typically the uninformed trader category. Did this decline have an impact on market quality? Earlier studies find that a decline in the OTR is accompanied by a decline in the market liquidity as well (Friederich and Payne, 2015; Malinova *et al.*, 2018). However, 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 these impacts in the next section.

5.3 Impact on liquidity

We present the DiD regression estimation results for liquidity measures for Event 1 and 2 in Table 8 and 9 respectively.

We find that the treatment effect captured by the $\hat{\beta}_3$ coefficient is significant across all liquidity measures in Panel A (8) 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 after Event 1. QSPREAD dropped by 6 basis points and the impact cost measures dropped in the range of 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 Event 1 fee on market liquidity. These findings reject 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 *et al.*, 2018).[20]

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

Table 8 DiD estimates for the impact of the OTR 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 Control Spot while Panel B presents the results for Treated spot and Control 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. ** values indicate statistical significance at 5% level.

	QSpread	IC_{250k}	IC_{500k}	IC_{1000k}	TOP1DEPTH	TOP5DEPTH	TOP7DEPTH	TOP10DEPTH	ILLIQ
Panel A: Treated SSF - Control spot									
Fee	0.006	-0.014	-0.016	0	0.029	0.043	0.047	0.04	-0.235
	(1.906)	(-1.936)	(-1.762)	(0)	(0.815)	(1.156)	(1.261)	(1.064)	(-0.576)
Treated	0.131**	-0.025	-0.043	0.027	1.902**	1.692**	1.675**	1.665**	-1.22
	(9.475)	(-1.19)	(-1.786)	(1.047)	(19.112)	(18.833)	(18.767)	(18.808)	(-1.487)
Treated×Fee	-0.06**	-0.032**	-0.047**	-0.103**	0.131**	0.145**	0.138**	0.136**	-1.178**
	(-6.799)	(-2.713)	(-3.411)	(-5.785)	(2.529)	(2.587)	(2.486)	(2.507)	(-2.078)
Market cap	-0.013	-0.02	-0.023	-0.03**	0.047	0.059	0.055	0.049	-0.54
	(-1.859)	(-1.774)	(-1.874)	(-2.188)	(1.124)	(1.254)	(1.155)	(1.023)	(-1.251)
Inverse Price	-0.001	-0.001	0	0.002	0.025**	0.031**	0.029**	0.027**	-0.04
	(-0.777)	(-1.215)	(-0.099)	(1.07)	(2.258)	(3.831)	(3.709)	(3.63)	(-0.928)
Market Vol	0.002**	0.004**	0.005**	0.006**	-0.011**	-0.014**	-0.014**	-0.015**	0.162**
	(9.351)	(13.52)	(13.233)	(9.82)	(-7.676)	(-10.059)	(-9.844)	(-9.967)	(7.726)
AT intensity	-0.001	-0.001	0	0	-0.002	-0.002	-0.003	-0.003	-0.004
	(-1.561)	(-1.633)	(-0.668)	(0.192)	(-0.613)	(-0.871)	(-0.954)	(-0.903)	(-0.157)
Rollover	0.012**	-0.001	-0.007	0	0.116**	0.132**	0.13**	0.126**	-0.174
	(2.377)	(-0.186)	(-0.885)	(0.031)	(5.132)	(4.989)	(4.667)	(4.299)	(-0.332)
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	-0.003	-0.017**	-0.018**	-0.006	-0.018	0.01	0.014	0.005	-0.302
	(-1.026)	(-2.216)	(-1.963)	(-0.551)	(-0.544)	(0.265)	(0.367)	(0.133)	(-0.741)
Treated	-0.012	-0.065**	-0.072**	-0.042**	0.379**	0.394**	0.354**	0.31**	-2.097**
	(-1.896)	(-3.506)	(-3.305)	(-2.063)	(4.36)	(4.663)	(4.161)	(3.626)	(-2.795)
Treated×Fee	0.002	0.009	0.006	-0.008	0.192**	0.184**	0.192**	0.208**	0.358
	(0.704)	(0.935)	(0.525)	(-0.616)	(3.899)	(3.502)	(3.52)	(3.714)	(0.742)
Market cap	-0.002	-0.018	-0.023**	-0.027**	0.166**	0.153**	0.152**	0.147	-0.481
	(-0.646)	(-1.855)	(-2.052)	(-2.279)	(2.276)	(2.122)	(2.056)	(1.956)	(-1.267)
Inverse Price	0	0	0.001	0.004**	0.04**	0.042**	0.041**	0.039**	-0.03
	(0.516)	(-0.247)	(0.723)	(2.136)	(5.36)	(7.274)	(7.33)	(7.396)	(-0.807)
Market Vol	0.001**	0.004**	0.004**	0.004**	-0.014**	-0.015**	-0.016**	-0.016**	0.141**
	(9.564)	(12.857)	(13.008)	(9.496)	(-10.293)	(-10.052)	(-9.696)	(-9.805)	(7.293)
AT intensity	0**	-0.001**	-0.001	-0.001	0.008**	0.007**	0.007**	0.007**	-0.025
	(-3.459)	(-2.309)	(-1.776)	(-1.322)	(2.936)	(2.458)	(2.292)	(2.292)	(-1.11)
Rollover	-0.002	-0.014**	-0.019**	-0.016**	0.092**	0.095**	0.093**	0.088**	-0.438
	(-1.407)	(-6.393)	(-5.366)	(-3.69)	(6.255)	(5.158)	(4.718)	(4.192)	(-1.433)
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

A possible reason for the improvement in market liquidity on the SSF market could be the 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 decline in aggregate OTR level primarily came from the reduction in the OTR of retail (NINP) traders. Given the nature of trading by retail traders, a reduction in order submissions by NINP traders would lower the fraction of unproductive orders in the market. We did not see any impact of the fee on the OTR levels of the institutional and proprietary traders. Since these traders are recognized as liquidity suppliers (Aitken *et al.*, 2007), we argue that the increase in SSF liquidity came from the lower number of order submissions by retail (NINP) traders.

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. But there is a positive impact on the depth of these stocks across all levels. The higher depth on the spot market for the treated stocks could be attributed to the the increased trading by both retail (NINP) and proprietary traders. Another possible channel could be the improved liquidity of the SSF market which may have resulted in increased trading on the underlying spot market. While we cannot empirically test these possibilities without examining traders' strategies, our findings conclusively show that market liquidity affected both the SSF and the spot market after Event 1, thus validating 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.

We now discuss the direct and indirect impact of Event 2 fee on market liquidity. Panel A in Table 9 presents the DiD regression estimation results for the impact on the SSF market for the OTR fee of Event 2. The treatment effect for QSPREAD is statistically significant, with a negative value of $\hat{\beta}_3$. This implies a reduction in the quoted half spread of Treated SSF relative to the Control spot. However, there is no similar improvement in liquidity is not seen in any other measure of transactions costs or depth. Thus, we do not find strong evidence of liquidity improvement on the SSF market after Event 2. This result is not surprising because the 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 Treated 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

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. ** values indicate statistical significance at 5% level.

	QSpread	IC_{250k}	IC_{500k}	IC_{1000k}	top1depth	top5depth	top7depth	top10depth	illiq
Panel A: Treated (SSF) - Control (Spot)									
Fee	-0.007**	-0.031**	-0.036**	-0.028**	0.086	0.104	0.113**	0.118**	-0.964**
	(-2.811)	(-4.066)	(-3.826)	(-2.169)	(1.764)	(1.881)	(2.052)	(2.209)	(-2.656)
Treated	0.108**	-0.038**	-0.046**	0.025	2.124**	1.802**	1.76**	1.752**	-1.755**
	(8.697)	(-2.22)	(-2.004)	(0.704)	(16.782)	(14.23)	(13.788)	(13.816)	(-2.626)
Treated×Fee	-0.039**	-0.007	-0.015	-0.058	0.094	0.136	0.122	0.101	0.092
	(-3.202)	(-0.46)	(-0.762)	(-1.927)	(1.042)	(1.398)	(1.249)	(1.053)	(0.159)
Market cap	-0.006	-0.021**	-0.022**	-0.018	0.148**	0.132**	0.142**	0.146**	-0.678**
	(-1.547)	(-3.885)	(-3.203)	(-1.659)	(3.45)	(2.259)	(2.312)	(2.344)	(-3.14)
Inverse Price	0.002**	0.002**	0.003**	0.007**	0.026**	0.023**	0.021**	0.02**	0.067
	(7.924)	(2.785)	(2.587)	(2.805)	(4.567)	(3.975)	(3.668)	(3.42)	(1.906)
Market Vol	0.001**	0.001**	0.001**	0.002**	-0.003**	-0.004**	-0.003**	-0.003**	0.034**
	(5.962)	(6.276)	(4.525)	(4.167)	(-3.921)	(-4.173)	(-3.8)	(-3.741)	(2.502)
AT intensity	-0.001**	-0.001**	-0.001**	-0.001**	-0.002	-0.003	-0.003	-0.003	-0.014
	(-3.937)	(-2.106)	(-2.176)	(-1.985)	(-0.839)	(-1.211)	(-1.198)	(-1.305)	(-1.154)
Rollover	-0.003	-0.006	-0.014	-0.031	-0.002	-0.017	-0.009	-0.016	-0.362
	(-1.812)	(-1.155)	(-1.582)	(-1.63)	(-0.058)	(-0.449)	(-0.237)	(-0.474)	(-0.945)
Excluded	0.052**	0.037	0.056**	0.105**	-0.252	-0.319**	-0.31	-0.27	1.231
	(3.003)	(1.771)	(2.029)	(2.267)	(-1.676)	(-2.006)	(-1.944)	(-1.744)	(1.342)
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 (Spot) - Control(Spot)									
Fee	-0.006**	-0.027**	-0.031**	-0.022	0.08	0.101	0.111**	0.118**	-0.96**
	(-2.602)	(-3.534)	(-3.29)	(-1.656)	(1.595)	(1.801)	(1.985)	(2.167)	(-2.637)
Treated	-0.001	-0.015	0.003	0.082**	0.32**	0.338**	0.337**	0.353**	-0.565
	(-0.18)	(-0.879)	(0.132)	(2.23)	(3.033)	(3.057)	(2.989)	(3.084)	(-0.835)
Treated×Fee	-0.004	-0.016	-0.028	-0.056**	0.193**	0.18	0.186	0.188**	-0.237
	(-1.285)	(-1.382)	(-1.876)	(-2.054)	(2.173)	(1.867)	(1.929)	(1.963)	(-0.498)
Market cap	-0.003	-0.027**	-0.03**	-0.025	0.197**	0.177**	0.183**	0.183**	-0.786**
	(-1.624)	(-4.603)	(-4.138)	(-1.874)	(3.025)	(2.318)	(2.336)	(2.295)	(-3.821)
Inverse Price	0.002**	0.002**	0.004**	0.007**	0.032**	0.027**	0.025**	0.023**	0.086**
	(15.937)	(3.393)	(3.15)	(3.061)	(5.971)	(5.02)	(4.659)	(4.316)	(2.713)
Market Vol	0.001**	0.002**	0.002**	0.003**	-0.008**	-0.007**	-0.007**	-0.007**	0.032**
	(9.059)	(8.111)	(5.657)	(2.908)	(-6.649)	(-5.682)	(-5.487)	(-5.397)	(2.071)
AT intensity	0**	0	0	0	0.003	0.001	0.001	0.002	-0.01
	(-2.458)	(-1.219)	(-1.312)	(-0.304)	(1.204)	(0.458)	(0.573)	(0.644)	(-1.076)
Rollover	-0.002**	-0.004	-0.007	0.006	0.013	-0.018	-0.011	-0.012	-0.448**
	(-1.972)	(-1.411)	(-1.409)	(0.226)	(0.674)	(-0.726)	(-0.445)	(-0.544)	(-1.977)
Excluded	0.009	0.055**	0.067**	0.164**	-0.372**	-0.393**	-0.417**	-0.441**	1.704**
	(1.831)	(2.866)	(2.678)	(2.246)	(-2.63)	(-2.503)	(-2.63)	(-2.778)	(2.172)
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

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, our analysis suggests that liquidity in the markets benefited from the 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. This improvement came via a reduction in the orders placed by retail traders on the SSF market, which reduced the number of unproductive orders in the market and brought back the genuine liquidity providers to the market. In contrast, in the second event, though the regulator had little success in using the fee to reduce the average OTR levels in the market, it does 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

We now turn to the results on the impact on the efficiency measures described in Section 4.1. Table 10 and 11 present the DiD estimations results for Event 1 and Event 2 respectively.In both the tables, Panel A presents the results of the direct impact on the Treated SSF relative to the Control spot, while Panel B presents the results for the indirect impact on the Treated spot.

$\hat{\beta}_3$ is significant for all the efficiency measures in Panel A for Event 1. All the four volatility measures are negative, showing decreased levels of returns volatility and liquidity risk for the Treated SSF relative to the Control spot. This reduction could be attributed to reduced retail (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.

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. In terms of the indirect impact, we do not find any evidence of the impact 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.

With regard to Event 2, we do not see a consistent change in $\hat{\beta}_3$ in Table 11. The coefficient

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. ** values indicate statistical significance at 5% level.

	σ_r	$\sigma_{\mathrm{IC},250k}$	$\sigma_{\mathrm{IC},500k}$	$\sigma_{\mathrm{IC},1000k}$	$\lvert VR-1\rvert$
Panel A: Treated (SSF) - Control (Spot)					
Fee	0.411	-0.003	0.005	0.016	-0.002
	(0.806)	(-0.442)	(0.439)	(1.665)	(-0.815)
Treated	12.59**	-0.008	-0.018	0.071**	-0.163**
	(5.949)	(-0.358)	(-0.766)	(3.425)	(-19.842)
Treated ×Fee	-7.472**	-0.048**	-0.065**	-0.106**	0.012**
	(-5.734)	(-4.15)	(-4.552)	(-6.902)	(2.284)
Market cap	-2.085	-0.015	-0.012	-0.012	0.006
	(-1.871)	(-1.447)	(-1.138)	(-1.342)	(1.138)
Inverse Price	-0.068	-0.003**	-0.003**	-0.002**	0.001
	(-0.717)	(-2.781)	(-2.972)	(-2.248)	(0.889)
Market Vol	0.466**	0.003**	0.003**	0.003**	-0.001**
	(12.748)	(8.703)	(8.146)	(8.678)	(-6.881)
AT intensity	-0.09	0	0	0	0
	(-1.654)	(-0.247)	(0.397)	(-0.164)	(-0.013)
Rollover	1.098	0.021**	0.017	0.039**	-0.004
	(1.657)	(2.038)	(1.441)	(2.606)	(-0.607)
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	-0.758	-0.005	0.003	0.012	0.001
	(-1.563)	(-0.663)	(0.306)	(1.362)	(0.48)
Treated	-3.304**	-0.037	-0.047**	0.008	0.002
	(-2.717)	(-1.905)	(-2.22)	(0.444)	(0.676)
Treated×Fee	0.449	-0.006	-0.01	0.001	-0.002
	(0.749)	(-0.637)	(-0.744)	(0.046)	(-0.496)
Market cap	-0.821	-0.013	-0.011	-0.008	0.005
	(-1.197)	(-1.38)	(-1.087)	(-0.939)	(1.872)
Inverse Price	-0.015	-0.002**	-0.003**	-0.003**	0.002**
	(-0.259)	(-2.699)	(-3.559)	(-4.058)	(8.447)
Market Vol	0.267**	0.002**	0.003**	0.002**	-0.001**
	(15.071)	(8.318)	(8.066)	(8.831)	(-7.009)
AT intensity	-0.08**	-0.001	0	-0.001**	0
	(-2.924)	(-1.139)	(-0.64)	(-2.014)	(-0.207)
Rollover	-0.424	-0.011**	-0.013**	-0.004	0.005
	(-1.959)	(-2.902)	(-2.218)	(-0.444)	(1.65)
Adjusted R^2	0.16	0.1	0.09	0.04	0.1
# of obs	6715	6713	6689	6358	6715

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. ** values indicate statistical significance at 5% level.

	σ_r	$\sigma_{\text{IC},250k}$	$\sigma_{\text{IC},500k}$	$\sigma_{\text{IC},1000k}$	$\lvert VR-1\rvert$
Panel A: Treated (SSF) - Control (Spot)					
Fee	-1.408**	-0.026**	-0.028**	-0.001	-0.001
	(-3.065)	(-3.213)	(-2.395)	(-0.176)	(-0.2)
Treated	12.583**	-0.021	-0.025	0.07**	-0.127**
	(6.515)	(-1.285)	(-1.182)	(4.21)	(-17.694)
Treated×Fee	-5.569**	-0.001	-0.01	-0.051**	0.011
	(-2.988)	(-0.071)	(-0.599)	(-2.959)	(1.36)
Market cap	-1.15	-0.007	-0.005	-0.002	0.013**
	(-1.779)	(-1.331)	(-0.804)	(-0.245)	(3.205)
Inverse Price	0.263**	0.001	0.001	0.001**	0.002**
	(7.099)	(1.184)	(1.248)	(2.487)	(9.772)
Market Vol	0.094**	0.001**	0.001**	0.001**	0
	(4.316)	(3.629)	(2.023)	(3.287)	(-0.222)
AT intensity	-0.093**	0	0	0	0
	(-3.482)	(-0.857)	(0.442)	(-1.421)	(1.525)
Rollover	-0.414	0.008	-0.008	0.009	-0.006
	(-0.921)	(1.34)	(-1.121)	(0.7)	(-1.359)
Excluded	7.71**	0.043**	0.06**	0.081**	-0.01
	(3.025)	(2.474)	(3.085)	(3.516)	(-0.938)
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	-1.162**	-0.024**	-0.026**	0.004	0
	(-2.729)	(-2.976)	(-2.182)	(0.569)	(0.04)
Treated	-1.432	-0.019	-0.014	0.093**	0.005
	(-1.784)	(-1.199)	(-0.603)	(3.259)	(0.981)
Treated×Fee	-0.646	-0.005	-0.013	-0.045	0.008
	(-1.067)	(-0.435)	(-0.801)	(-1.835)	(1.717)
Market cap	-0.658**	-0.005	-0.005	-0.004	0.006**
	(-2.133)	(-1.247)	(-0.806)	(-0.385)	(3.193)
Inverse Price	0.29**	0.001	0	0	0.002**
	(11.591)	(1.575)	(0.918)	(0.035)	(13.353)
Market Vol	0.11**	0.001**	0.001**	0.002**	0
	(7.689)	(5.709)	(2.903)	(3.025)	(-1.202)
AT intensity	-0.024	0	0	0	0**
	(-1.881)	(-0.371)	(0.385)	(-0.882)	(4.982)
Rollover	-0.333	0.002	-0.003	0.012	-0.009**
	(-1.549)	(0.503)	(-0.567)	(1.018)	(-2.956)
Excluded	2.271**	0.053**	0.077**	0.084	-0.021**
	(2.472)	(3.365)	(3.32)	(1.675)	(-2.957)
Adjusted R^2	0.58	0.09	0.03	0.04	0.21
# of obs	9515	9512	9415	8223	9515

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 worldwide increasingly are adopting measures to slow down high frequency trading. Such measures range from fees and taxes to design innovations such as randomized speed bumps and minimum resting times for orders. However, empirical evidence has been mixed in their impact on market quality.

We exploit a unique opportunity in the Indian equity markets to explore reasons behind such mixed results. We analyse the impact of an order to trade fee that was introduced at two different times but implemented differently. In one event, the exchange used the fee to manage infrastructure load and applied it uniformly across all orders. In the other, the regulator imposed the fee selectively on orders away from the market, hoping to penalize manipulative but not market making orders.

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 differences-in-differences 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.

The data that we use is also unique compared to similar trades and quotes or trades and orders data from other exchanges globally. In the data published by the NSE, each order is flagged as coming from an algorithmic or a non-algorithmic source. Additionally, each order is flagged as an institutional order, a proprietary securities firm order, or a retail order which is neither institution nor proprietary. If we follow standard practice in categorising retail traders as most likely to be uninformed traders, then this data-set offers some of the best classification of trades and orders data into algorithmic orders from informed and uninformed traders. This allows us to link the impact of the OTR fee to market outcomes through the channel of changes in the behavioural choices of traders.

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 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 during either event.

These results provide additional insight to understanding the mixed results recorded by earlier literature on the impact of such interventions. A recent study at the Oslo Stock Exchange also confirms the ineffectiveness of such a fee when it is applied selectively (KjellJørgensen *et al.*, 2018). While it is tempting for regulators to intervene in markets, it is equally important for them to design such interventions so as to achieve their primary objective. By exempting liquidity enhancing orders, presumably not to worsen market quality, the regulator seemed to have rendered the fee ineffective in slowing down these fast traders. Not only does this defeat the primary purpose of this fee, it also provides a false sense of security to the regulator and to the public that the market is now being protected well.

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.

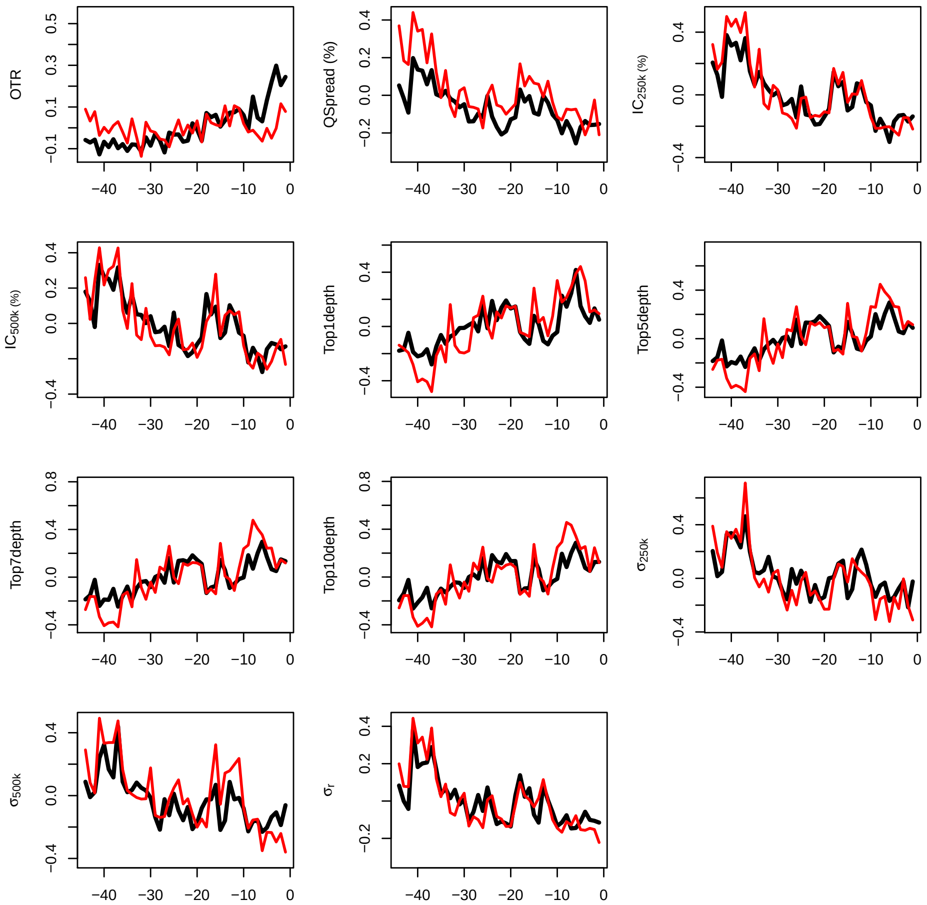

Figure A2 Pre-treatment outcome variables for matched treated and control stocks on the spot market around Event 2

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.