When is the Order to Trade fee effective?

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Abstract

Regulators use measures such as a fee on high order to trade ratio (OTR) to slow down high frequency trading. Their impact on market quality is, however, mixed. We study a natural experiment in the Indian stock market where such a fee was introduced twice, with differences in motivation and implementation. Using a difference-in-difference approach, we find that the fee decreased OTR and improved market quality when it was imposed on all orders, while it had little effect when it was imposed selectively on some orders. Improvement in liquidity was driven by a reduction in adverse selection costs following lower OTR.

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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. 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 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; Carrion, 2013; Boehmer *et al.*, 2018; Brogaard *et al.*, 2014; Chaboud *et al.*, 2014).

However, increased trading activity induced by high frequency trading has also become a source of heightened concern. Policy makers and public opinion view high levels of trading activity in financial markets as 'excessive noise', leading to regulators and exchanges to propose interventions to slow down such trading. An early example of such an intervention is the securities transactions tax (Tobin, 1978), which several exchanges have experimented with at different times. A more recent example is the introduction of tiny delays in high frequency order placement (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 document that such interventions have often had an adverse effect. 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. Rather, the tax resulted in lower liquidity. Chen *et al.* (2017) find that the introduction of speed bumps at the TSX Alpha in Canada worsened the market quality not just on TSX Alpha but also on other venues that did not introduce the speed bump.[2] Despite such evidence, the search for an effective intervention to bring down trading activity continues.

In recent times, an intervention to disincentivise excessive order placement activity is the *orders-to-trades ratio* (OTR) fee. The OTR fee is a charge to a trader when her ratio of orders to trades crosses a fixed threshold. The Chicago Mercantile Exchange (CME) in 2005 was the first time that an exchange was observed to use this fee.[3] Since then, more

[1] The Investor's Exchange in the U.S. or IEX (`https://iextrading.com`) was the one of the first exchanges to implement a 350 micro-seconds time delay. More exchanges are following the IEX in the US, like Deutsche Borse, Intercontinental Exchange, London Metal Exchange, 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] Anderson *et al.* (2021) also examine the introduction of the speed bump at TSX Alpha and find mild improvements in liquidity, at a significant loss in market share for the exchange.

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

exchanges have used the OTR fee to slow down high frequency trading. These include the Italian Stock Exchange, 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, Jorgensen *et al.* (2018) find that an OTR 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 design features of the fee, where it was exempted for liquidity improving orders.

Our study is motivated by a desire to reconcile these different results. In this paper, we examine two instances when the OTR fee was imposed on trading at the National Stock Exchange (NSE) of India. The objectives as well as the design of the fee across the two implementations were different. The first implementation was during the early days of algorithmic trading, when the exchange introduced the fee to manage the high load on its limited infrastructure. The second implementation was when algorithmic trading was well established, and there were heightened public policy concerns about algorithmic trading leading to excessive trading activity. The regulator implemented the OTR fee in response to these concerns. Being driven by different objectives, the design of the fee also varied: 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. In both cases, the fee was imposed only on equity derivatives, and not on the underlying stock that trades on the spot market. These variations across these two episodes offer a unique opportunity to study how the nature of the intervention affects the outcomes.

We obtain proprietary tick-by-tick 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 traders: institutional, proprietary and non-institutional-non-proprietary. Of these, the third category is a catch-all category that includes a variety of informal fund managers along with retail traders. These features of the data allow us to analyse the impact of the intervention on trader behavior across different trader categories, and thus helps us trace the source of the observed impact 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 80 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.[4]

[4]When costs of trading increases on one venue, trading shifts to alternative venues (Brunnermeier and Pedersen, 2009; Aggarwal and Thomas, 2019).

We set up a difference-in-difference regression framework to understand the casual impact of the OTR fee. Since the fee was only imposed on derivatives trading, one candidate for the control set is the underlying stock. However, SSF and its underlying stock are exposures on the same asset, albeit with different leverage and liquidity trade-offs. 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.*, 2020b). 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 a 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 direct impact of the fee by comparing the changes in the 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 implemented the fee to disincentivise traders from excessive loading on the trading system, it managed to achieve a lower aggregate OTR on the SSF market. We also find that reduction in aggregate OTR did not lead to lower liquidity, contrary to the results obtained in other studies (Friederich and Payne, 2015; Malinova *et al.*, 2018). In fact, we observe an improvement in liquidity after the intervention for the treated stocks on the SSF market. These results are supplemented by a loss of short-term efficiency that dissipates over longer intervals.

We argue that the improvement in market liquidity came from a reduction in unproductive orders that clogged the market queue, and imposed high cost on other liquidity suppliers. In response to the fee, we find a significant decline in the OTR levels of the non-institutional-non-proprietary category of traders. This category generated a third of all algorithmic orders, suggesting that it may not be retail traders who are generating these unproductive orders (Barber *et al.*, 2009; Foucault *et al.*, 2011). The aggregate OTR levels of the institutional and proprietary traders do not show any significant change.

Following Brogaard *et al.* (2015), we examine the channel(s) through which unproductive orders could impact liquidity. In particular, we examine two channels – cost associated with adverse selection and revenue from managing inventory – that directly affect the incentives of liquidity suppliers. Traders who can trade or cancel faster reduce (increase) the chance of slower liquidity suppliers trading during favourable (adverse) market conditions. In other words, they exacerbate the adverse selection costs for liquidity suppliers. Similarly, the inability to predict executions because of order stuffing by traders placing unproductive orders could lead liquidity suppliers to carry unwanted inventory risk. This may hurt their ability to offer liquidity and cause them to demand higher revenues.

We see a significant reduction in the adverse selection cost (about 180 bps) for liquidity suppliers after the imposition of the fee, suggesting that disincentivizing unproductive orders indeed helped reduce the risk for liquidity suppliers in the market. Interestingly, liquidity suppliers among both proprietary and the non-institutional-non-proprietary traders experienced reduction in their adverse selection cost, indicating that not all traders in the latter category were sending unproductive orders.[5] However, the reduction in adverse selection cost in proprietary orders was roughly 1.8 times the reduction seen in the orders from non-institutional-non-proprietary traders. This suggests that the bigger beneficiaries were indeed proprietary traders who were acting as market makers. We do not see any change in the revenues of managing inventory for liquidity suppliers driven by the fee suggesting that unproductive orders were hurting liquidity suppliers mainly by exacerbating their adverse selection cost.

In terms of the indirect effects of the OTR fee, 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 the increase comes from the non-institutional-non-proprietary and proprietary trader categories. The findings suggest that traders switched high OTR-related trading strategies from the more expensive venue (SSF where the fee was imposed) to the cheaper venue (spot market where the fee was not applicable). This substitution, though did not have any impact on transactions costs and efficiency measures, positively affected the relative depth of the treated stocks on the spot market.

We find no impact of the OTR fee on the aggregate OTR level when the regulator implemented the fee driven by public policy concerns. The fee in this episode was applied with exemptions, one of which was that the fee would not apply on orders placed within the one percent price limit of the last traded price. A likely response by traders would be to modify trading strategies to shift orders to within the one percent price limit threshold. This response would manifest as lower number of orders placed outside the threshold and a higher number of order placed closer to the last traded price. Indeed, we observe a lower percentage of orders outside the threshold on both the SSF and spot market after the intervention. However, this change in trading behavior did not impact market liquidity or price efficiency.

Our findings suggest that an intervention which is designed to correct an identified market failure, taking into account trader incentives, is more likely to achieve its intended outcome. In our study, we observe little to no impact when the intervention was driven purely by regulatory concerns, a common feature that drives OTR fee interventions against algorithmic trading across the world. The microstructure setting of the Indian equity market used in identifying the treated and control groups avoids some endogeneity issues and strengthens the causal inference of our results. The paper adds to the growing body of lit-

[5] Institutions were a small percentage of the NSE derivatives market at this time owing to regulatory constraints. Banks, Insurance and Pension Funds were not permitted to participate in equity derivatives, and Mutual Funds were disincentivised from participating by regulation.

erature about the effect of micro-structure interventions on trading behaviour and, in turn, on market outcomes. This is especially relevant as regulators worldwide are increasingly seeking optimal interventions to curb high frequency trading.

The paper is organised as follows: Section 2 discusses regulatory interventions on high frequency trading and its impact on market quality. This is followed by a discussion of testable hypotheses 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 Regulatory interventions on high frequency trading

Algorithmic trading (AT) and high frequency trading (HFT) have become the dominant form 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 over the 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,[6] and the crash at the NSE because of a fat-finger trade in the "Nifty" index futures in October 2012.[7]

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 not seen as providing genuine liquidity. The empirical evidence on the incidence of market manipulation in AT and HFT is sparse because such analysis requires information on trader-identifiers which is not readily available. Few studies such as Egginton *et al.* (2016), Gai *et al.* (2012) and Van

[6]'After Panic, Tokyo market rebounds', *The New York Times*, 19 January 2006.
[7]'Emkay admits error in Nifty crash; stock tanks 10%', *Mint*, October 2, 2012.

Ness *et al.* (2015) use indirect proxies and find evidence of higher quote stuffing activity. Manahov (2016) uses simulations and finds that HFT scalpers front-run the order flow, damaging market quality and the interests of long-term investors. Such evidence, along with the heightened fears of manipulative strategies such as layering, spoofing, and quote stuffing using HFT, has prompted regulators to search for interventions against such forms of market abuse.

The interventions that are most widely implemented to slow down AT and HFT are of two types: barriers in the trading mechanism and a penalty or fee on the use of 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 mislead other traders. In the last few years, several exchanges have experimented with the OTR fee to curb HFT including the CME, the Canadian Stock Exchange, the Italian Stock Exchange and the Oslo Stock Exchange.

But 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 leads 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. Jorgensen *et al.* (2018) find that the fee did not cause any adverse changes to average liquidity at the Oslo stock exchange, but do not find any benefits from the fee either.

Such mixed evidence raises questions about the scenarios under which the fee achieves its intended objective and when it fails to deliver. In order to understand this, we outline the channels through which such a fee can be effective in the next section.

2.1 Hypothesis development

The OTR fee impacts market outcomes through trader incentives. Changes in costs through an OTR fee can align trader incentives to refrain from sending 'unproductive, noisy' orders to the market or order that may be manipulative in nature. But the effectiveness of the fee depends on whether it is binding and on whom. If the fee is binding for traders with high OTR, traders will change their trading behavior to lower their OTRs. On the contrary, if the fee is not binding, it will not induce any changes in trader behaviour and the OTR levels will remain unchanged.

An example of when the fee may not be binding is if the thresholds at which the fee is applicable are set too high. Or if the fee itself is set too low. Another example is if the fee is imposed differently on different participants, or differently at various levels of the limit order book. In such cases, traders can effectively avoid higher costs due to the OTR fee by changing their trading behaviour so that the fee is effectively not binding. This leads to the following hypothesis:

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

A second channel through which the OTR fee can be effective is to see what type of trading activity it restricts. A large number of unproductive orders place negative externality on the remaining market participants by clogging the bandwidth of the exchange, and increasing market latency. This keeps out genuine traders from participating in the market and reduces the overall market liquidity. If the fee is correcting the negative externality, it can bring back such traders into the market. Additionally, 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 expect a negative impact on liquidity and price efficiency.[8] An OTR fee can reduce the ability of liquidity providers to rapidly update their orders in changing market conditions. Malinova *et al.* (2018) documents such an adverse impact of the fee on market liquidity. Lower market liquidity could negatively impact price efficiency through an adverse impact on the profitability of informed traders (Bloomfield *et al.*, 2009).

The above discussion suggests that the impact of the OTR fee could either be positive or negative, depending on which participants and orders it targets. This leads to the following two competing hypotheses:

> **Hypothesis 2A:** If the fee is effective in ensuring that only excessive orders from noise traders are deterred, then liquidity and price efficiency will improve after the fee imposition.

> **Hypothesis 2B:** If the fee adversely impacts liquidity providers and informed traders, liquidity and price efficiency will worsen after the fee imposition.

Lastly, an OTR fee can change the patterns of trading on competing and complementary trading venues. (Colliard and Hoffmann, 2017) argue that an increase in trading costs on one venue can lead to participants shifting to the cheaper venue. If the two venues are similar in terms of liquidity, then a fee that is binding can result in migration of trading from the venue with the OTR fee to the one without the fee. If the two venues are interlinked by arbitrage, price efficiency and market liquidity of both venues can be impacted similarly even if the OTR fee is only implemented on one venue. This leads to the last set of hypotheses:

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

Hypothesis 3A: If two venues compete for liquidity, then an OTR fee imposed in one leads to improved liquidity in the other.

Hypothesis 3B: The fee can indirectly impact market liquidity and price efficiency in the *same* direction for all venues that are linked by arbitrage, even if the fee is implemented only in one venue.

Next, we present the context and the data within which we attempt to test these hypotheses.

3 Indian equity markets and OTR fee regimes

Our analysis uses the microstructure features and data from the equity trading platforms of the National Stock Exchange of India (NSE). The NSE is the dominant exchange for equity spot and derivatives trading in India[9] 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 January 2020, it was the world's largest derivatives exchange by volume.[10] The single stock options volumes have started rising only in recent years,[11] contrary to the trends in the U.S equity markets where single stock options trading dominate equity derivatives trading activity.

However, much else about the microstructure at the NSE is similar to the global exchanges for equity and equity derivatives. Trading takes place on an anonymous, continuous, electronic limit order book market. Orders are matched with a price-time priority. Market trading hours are from 9:00 am to 3:30 pm, with opening prices being determined through a pre-open call auction that runs 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. Around 1800 stocks are listed on the equity platform of NSE, of which, derivatives instruments trade only on 166 stocks.[12] Derivatives 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.

Both the selection criteria and the final choice of securities for trading derivatives is strictly based on permissions from the regulator, the Securities and Exchanges Board of India (SEBI). Algorithmic trading (AT) on equity and equity derivatives was permitted by SEBI in April 2008, while co-location was introduced only in 2010.

In September 2009, the NSE detected that there was a high rate of orders being placed on derivatives that rarely resulted in trades. To deter such orders from imposing an excessive

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

[10] *India now has world's largest derivatives exchange by volume*, Bloomberg, January 21, 2020.

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

[12] Data as of May 2019.

load on its infrastructure, the exchange levied a fee on a trading member if her OTR on equity derivatives trading crossed a stated threshold. The circular issued by the exchange stated the objectives of the fee as (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 (not just AT) and all order types, without exceptions.[13] A year later, the exchange issued a circular in June 2010 observing that there was a 'notable' reduction in the OTR in the derivatives segment, and both reduced the OTR fee as well as raised the minimum thresholds for daily OTR.[14]

By 2012, AT on Indian equity had increased to significant levels.[15] Concerned about the rising AT levels, SEBI directed the exchanges to impose an OTR fee on derivatives trading, in a circular in 2012, stating:[16]

> "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 imposed by SEBI was different from that imposed by NSE. It was applicable *only* on algorithmic orders. In addition, the application had several exceptions. For example, all orders that were placed or modified *within one percent* of the last traded price were exempt from the fee. Orders from *designated market makers* were exempt.[17] The reason stated for

[13] 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).

[14] See NSE (2010).

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

[16] See SEBI (2012a)

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

the exemptions was 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.

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% Last Traded Price (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.

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.

Our analysis examines the OTR fee impact around the first date when NSE imposed the OTR fee (NSE, 2009) and the third date when SEBI imposed the OTR fee (SEBI, 2012a; NSE, 2012).

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 event when the fee was imposed, as follows:[18]

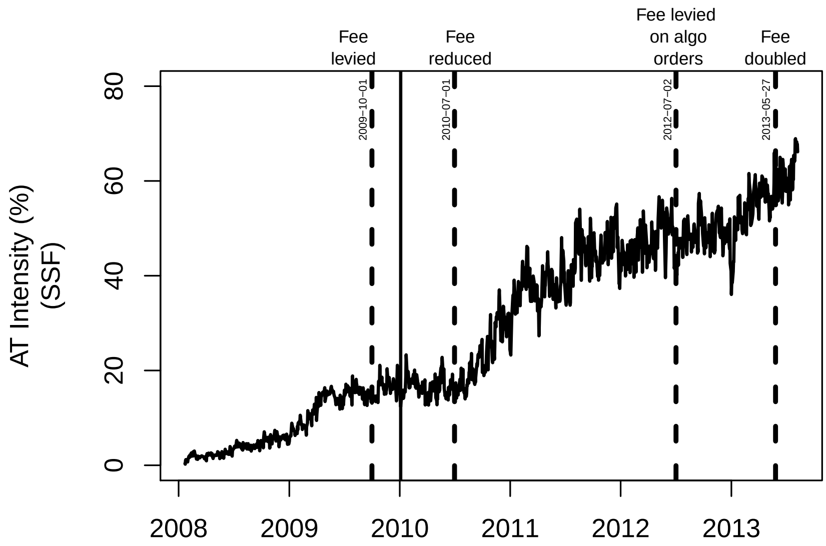
Event 1 when NSE imposed the fee on October 1, 2009

a) Pre event period: July 2009 to September 2009

[18]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.



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

We use proprietary, tick-by-tick orders and trades (TAO) data for the equity spot and the SSF segments of NSE during our sample periods.[19] Each trade and order is time-stamped to jiffy, with each order having a unique order-id that is retained during the entire trading day. This allows us to construct the full limit order book at every order update, and is used to calculate various market quality measures at intra-day level, as described in the following section.

In addition to the information on ticker, price and quantity for each order and trade, the data also include 'buy / sell' order tag, an 'order entry / order modification / order cancellation' tag, an 'AT / non-AT' tag,[20] and a trader type indicator of 'custodian', 'proprietary' and 'non custodian non proprietary'. The trader category 'custodians' includes

[19] This dataset is also used by Nawn and Banerjee (2018), Chakrabarty *et al.* (2019), Nawn and Banerjee (2019).

[20] In India, each trader using an algorithm is required to register herself as an algorithmic trader with

institutional investors, mutual funds, and financial institutions. This category represents institutions and is referred to as INST in the rest of the paper. The 'proprietary' category refers to traders who trade on their own account (referred to as PROP). The last category represents the remaining traders including retail traders, informal fund managers and private money managers. Since this category represents non-institutions and non-proprietary traders, we refer to it as NINP. It is useful to point out that this trader categorisation does not lead to a clean separation between who uses algorithms and who does not: each category has a mix of both. During the period of Event 1, around 26 percent of the orderflow in the overall markets came from AT. Of this, 17.4 percent was accounted for by PROP traders, and 8.59 percent by NINP.

4.1 OTR and market quality measures

To test Hypothesis 1, we need an *OTR* measure at stock-day level. We compute it as the ratio of total number of messages received on a stock to the 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.

The remaining hypotheses require market quality measures. We capture liquidity based on *transactions costs* and *depth* measures. We capture efficiency based on *variance ratios* and *short term volatility* measures.

We compute *transactions costs* using three measures: (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 two transaction sizes: Rs.250,000 (USD 3,800), and Rs.500,000 (USD 7,600).[21] 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).

We calculate four *depth* measures: (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

the exchange. The exchange then tags the IP of that trader as an algorithmic trader and all orders from such a trader are classified as algorithmic.

[21] 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.

seven prices (or TOP7DEPTH) and (4) the Rupee value of orders available across the best 10 prices (or TOP10DEPTH).

We compute the *variance ratio* or VR (Lo and MacKinlay, 1988) as the absolute value of the ratio of the variance of ten seconds log returns divided by two times the variance of five seconds 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.

We use *realised volatility* (σ_r) for each stock-day to measure *short term price volatility*, where σ_r is the standard deviation of intraday returns computed at every five seconds, scaled up by the square-root of the number of five second intervals in a trading day.

An argument often made against AT and HFT is that several AT and HFT orders are withdrawn before another trader can act upon it. This suggests such activity could lead to higher volatility of liquidity itself, and not just higher volatility of returns. Prior empirical literature suggests stock returns decrease with an increase in the volatility of liquidity. Pereira and Zhang (2010) develop a model that shows that rational investors prefer volatility in liquidity as they can adapt their trades to time varying liquidity. This suggests that lower volatility in liquidity could reduce the attractiveness, and hence, increase expected returns of the underlying stocks. To capture this aspect, we measure the volatility of liquidity (referred to as LIQVOL) by calculating the standard deviation of the impact cost at various order sizes.

All market quality measures except the ILLIQ measure are calculated using the complete limit order book constructed out of the TAO data. 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 framework 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 derivatives markets in India. One choice for the *control group* is the underlying stock since the fee was not applied on the spot market. 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 can result in an indirect impact of the fee on the underlying stock, and makes the underlying a sub-optimal / contaminated control (Boehmer *et al.*, 2020b).

We therefore construct an alternate control group based on stocks which do not have derivatives trading. Such stocks are likely to be least affected by the fee, either directly or indirectly. But they must match the treated group in terms of basic stock characteristics. We identify an alternate control group as those stocks that are close to, but do not satisfy, the criteria used by NSE for selecting stocks for derivatives trading:

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'[22] 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 use the above criteria in selecting the variables to match the treatment stocks (SSF) with the alternate control group.[23] In particular, we use market capitalisation ('market cap'), prices, floating stock, turnover and number of trades.[24] The covariate values are calculated as the average values for the period before the fee was announced.

To capture the multiple covariates in one dimension, we use propensity score matching approach where the scores are estimated using a logistic regression. 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. This group of 'matched non-derivatives' stocks form the *control* sample while stocks with derivatives trading constitute the *treated* sample.[25] Details of the matching exercise are presented in Section A of the Appendix.

The final sample for Event 1 has 39 matched treated and control stocks, while that for Event 2 has 41 matched treated and control stocks (Table 2). 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 3 presents the mean and standard deviation of each market quality variable for the matched samples during the pre-event period for both Event 1 and Event 2. '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 stocks traded on the spot market

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

[23] We remove stocks that underwent any corporate action including stock split, merger, rights and bonus issue or a buyback during the periods of our analysis.

[24] 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.

[25] 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.

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

(the underlying market) on which the fee was not imposed. 'Control spot' represents the set of matched control stocks which are traded on the spot market.

The OTR level of the Treated SSF is consistently higher compared to the OTR of the Treated spot as well as the Control spot. There are no consistent patterns in the differences between liquidity of the Treated SSF compared to the Treated spot or the Control spot, but volatility is higher for the Treated SSF.[26] We take these differences into account while constructing a differences-in-differences (DiD) framework that we discuss in the next section.

4.3 Differences-in-differences (DiD) specification

We use the following differences-in-differences (DiD) regression specification to measure the impact of the OTR fee:

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

where $\textsc{measure}_{i,t}$ is one of the OTR or market quality measures described in Section 4.1 for stock 'i' on day 't'. $\textsc{treated}_i$ 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. $\textsc{event}_t$ is a time dummy which takes the value of one for the period post the fee imposition, and zero otherwise.

[26]We note that the average value of |VR-1| for both the treated and control stocks on the spot market is high and a large departure from a random walk. We attribute this to the high frequency at which the VRs are computed (five-second returns). The spot market is less efficient for the treated and controls stocks at frequencies lower than one minute. We re-compute the VRs using five minutes returns (to ten minutes returns variance) and find the average value of the |VR-1| at 0.18 and 0.19 for the treated and control stocks, respectively.

Table 3 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 'Control spot' sets. The statistics for these variables for Event 1 (when the NSE imposed the OTR fee) are presented in Panel A, and statistics for the variables for Event 2 (when SEBI imposed the OTR fee) are presented in Panel B.

	Treated SSF		**Treated spot**		**Control spot**	
Market variable	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
TOP1DEPTH (log)	13.42	12.30	12.15	11.83	11.79	12.02
TOP5DEPTH (log)	15.32	14.53	14.22	13.88	13.83	13.95
TOP7DEPTH (log)	15.68	14.79	14.57	14.19	14.21	14.25
TOP10DEPTH (log)	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 (%)	14.47	5.03	6.92	1.89	9.44	4.41
|VR-1|	0.21	0.04	0.37	0.02	0.37	0.02
LIQVOL_{250k} (%)	0.15	0.07	0.12	0.05	0.18	0.13
LIQVOL_{500k} (%)	0.17	0.08	0.14	0.05	0.20	0.14
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
ILLIQ	3.81	3.21	4.74	3.83	5.86	4.25
TOP1DEPTH (log)	13.36	12.90	11.86	11.88	11.98	12.85
TOP5DEPTH (log)	15.23	14.79	14.06	14.16	14.07	14.78
TOP7DEPTH (log)	15.62	15.22	14.50	14.66	14.44	15.08
TOP10DEPTH (log)	16.03	15.63	14.94	15.14	14.80	15.37
σ_r (%)	13.84	6.29	6.92	3.15	8.18	3.78
|VR-1|	0.21	0.04	0.35	0.04	0.34	0.05
LIQVOL_{250k} (%)	0.13	0.06	0.13	0.05	0.16	0.09
LIQVOL_{500k} (%)	0.14	0.07	0.16	0.08	0.17	0.12

This variable accounts for possible differences that arise out of factors common to all stocks in the pre-event and post-event period. The interaction term coefficient, β_3, measures the causal impact of the fee on $\text{MEASURE}_{i,t}$ and is the coefficient of interest in our analysis.

We also include control variables to account for stock-specific variation and changes in macroeconomic conditions. Market cap ($\text{MCAP}_{i,t}$) and relative tick size measured by the inverse of the stock price ($\text{INVERSE-PRICE}_{i,t}$) capture stock specific variation. Market volatility, measured as the realised volatility of intra-day returns on market index (MARKET-VOL_t), is used to capture the effect of macro-economic conditions. ROLLOVER-DUMMY_t controls for rollover effects of trading positions shifting from near month to next month expiry. This dummy takes the value of one for the period two days prior to futures expiry and zero otherwise. We also include an $\text{EXCLUDED-DUMMY}_{i,t}$ for Event 2. This is to account for the sample stocks that were excluded from dervatives trading from October 2012.[27] Even though the exclusion date does not fall into our sample period, to eliminate the announcement effects, we include this dummy in all our Event 2 regressions.

All variables are winsorised at the 99% and 1% levels 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 measures 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 the outcome variables prior the imposition of the fee for each event (Colliard and Hoffmann, 2017). Figures B.1 and B.2 in the Appendix present evidence in favor of this assumption for both the OTR and market quality measures. Prior to the imposition of the fee, we observe a similar trend in all the variables for the treated and control groups across both the events.

5 Results

In this section, we discuss the estimation results for the main DiD regression (Equation (1)) to quantify the impact of the OTR fee imposed in Event 1 and Event 2, on OTR and market quality of the treated securities.

[27]In a circular dated July 23 2012 (SEBI, 2012b), SEBI revised the eligibility criteria for inclusion of stocks into derivatives segment. Some 51 stocks were excluded from derivatives trading as a result. However, the unexpired futures contract on these 51 stocks continued till September 2012. Our analysis period is from April to September 2012, and in our matched sample there were 23 stocks that were excluded (out of 41). Excluding them altogether from the analysis would reduce the sample size considerably. Since these 23 stocks continued to trade till the end of our analysis period on the derviatives market, we account for this exclusion using an exclusion dummy.

5.1 Impact on OTR

Table 4 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 × Event' is the interaction term that captures the estimated treatment effect ($\hat{\beta}_3$) of the fee on the level of OTR.
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
Event	0.066	0.046**	2.564**	1.604**
	(0.439)	(2.121)	(4.079)	(3.627)
Treated	24.736**	0.274**	60.914**	0.908
	(18.809)	(4.67)	(8.52)	(0.691)
Treated×Event	-4.211**	0.331**	7.669	4.243
	(-3.81)	(5.481)	(0.654)	(1.454)
Market cap	-0.255	0.047	0.512	0.599
	(-0.505)	(0.838)	(0.234)	(0.884)
Inverse Price	0.099	-0.022 **	-0.19	-0.106 **
	(1.52)	(-4.416)	(-1.855)	(-3.241)
Market Vol	-0.021	-0.003 **	0.246	-0.022
	(-0.911)	(-2.458)	(1.889)	(-1.803)
Rollover	5.695**	0.012	0.685	0.65**
	(4.008)	(0.524)	(0.596)	(1.992)
Excluded			-3.579	-6.167
			(-0.239)	(-1.605)
Adjusted R^2	0.63	0.33	0.26	0.12
# of obs	6060	6715	7485	9515

Table 4 presents the effect of the OTR fee on the aggregate OTR levels. Columns 2 and 3 in the table show the impact in Event 1, and Columns 4 and 5 show the impact in Event 2. We find that aggregate OTR levels *dropped* after the fee in Event 1. But there is *no change* on the average OTR level after the fee in Event 2.

In Event 1, the OTR level of treated stocks on the SSF market (Treated SSF) reduced by 4.211 units on average after the fee was implemented. This finding is consistent with Hypothesis 1 which says that a fee which is binding on traders will reduce the aggregate OTR level. $\hat{\beta}_3$ for the stocks underlying the SSF (Treated spot) is positive and significant, indicating a 0.33 units increase in the OTR level for these stocks relative to control stocks. These results suggests that there was both a direct impact (trading migrated to the spot market from the SSF) and an indirect impact (trading moved from the matched stocks) because of the fee.

In the case of Event 2, $\hat{\beta}_3$, is insignificant for the treated stocks and both the treated and control spot. This implies that the fee in Event 2 did not affect the aggregate OTR levels either directly or indirectly. Since the OTR fee in Event 2 was binding only on orders beyond 1 percent, we test for changes in OTR for these orders. The results are presented in Table 5. Not surprisingly, we find that there is a significant reduction in the OTR for those orders.

Table 5 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 × Event' is the interaction term that captures the causal effect ($\hat{\beta}_3$) of the fee on the OTR for the treated stocks.
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
Event	-1.545	-2.153
	(-1.023)	(-1.419)
Treated	-4.272	7.474**
	(-1.134)	(2.218)
Treated×Event	-13.116**	-8.749**
	(-4.173)	(-3.116)
Market Cap	-0.987	-0.705
	(-0.869)	(-0.563)
Inverse Price	0.386**	0.461**
	(4.287)	(4.141)
Market Vol	-0.004	-0.169**
	(-0.046)	(-3.776)
Rollover	1.174	2.07**
	(1.132)	(2.899)
Excluded	12.142**	11.252**
	(2.544)	(2.935)
Adjusted R^2	0.18	0.22
# of obs	7485	9514

These findings validate Hypothesis 1 that the fee was effective in changing trading behaviour when it was binding.

Did the fee have any impact on market quality, either directly or indirectly? Previous studies find that a decline in the OTR is accompanied by a decline in the market liquidity (Friederich and Payne, 2015; Malinova *et al.*, 2018). We test the impact of the fees on market liquidity and other aspects of market quality in the next two sections.

Table 6 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 × Event' ($\hat{\beta}_3$) captures the treatment effect.
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}	TOP1DEPTH	TOP5DEPTH	TOP7DEPTH	TOP10DEPTH	ILLIQ
Panel A: Treated SSF - Control spot								
Event	0.005	-0.016**	-0.017	0.025	0.038	0.042	0.035	-0.243
	(1.54)	(-2.188)	(-1.874)	(0.717)	(1.034)	(1.129)	(0.936)	(-0.623)
Treated	0.125**	-0.032	-0.046**	1.884**	1.668**	1.649**	1.64**	-1.255
	(9.513)	(-1.617)	(-2.029)	(20.978)	(20.062)	(19.939)	(19.859)	(-1.588)
Treated×Event	-0.058**	-0.03**	-0.046**	0.137**	0.153**	0.146**	0.144**	-1.167**
	(-6.888)	(-2.599)	(-3.408)	(2.739)	(2.778)	(2.683)	(2.687)	(-2.136)
Market cap	-0.013	-0.02	-0.024	0.046	0.058	0.054	0.048	-0.542
	(-1.862)	(-1.783)	(-1.878)	(1.106)	(1.239)	(1.139)	(1.006)	(-1.25)
Inverse Price	-0.001	-0.001	0.000	0.025**	0.031**	0.029**	0.027**	-0.04
	(-0.744)	(-1.178)	(-0.087)	(2.273)	(3.857)	(3.739)	(3.662)	(-0.927)
Market Vol	0.002**	0.004**	0.005**	-0.011**	-0.014**	-0.014**	-0.015**	0.162**
	(9.364)	(13.398)	(13.19)	(-7.786)	(-10.191)	(-9.971)	(-10.09)	(7.717)
Rollover	0.011**	-0.003	-0.008	0.11**	0.125**	0.123**	0.119**	-0.184
	(2.195)	(-0.557)	(-1.023)	(5.413)	(4.891)	(4.508)	(4.181)	(-0.36)
Adjusted R^2	0.46	0.18	0.19	0.83	0.81	0.8	0.8	0.06
# of obs	6060	6058	6037	6060	6060	6060	6060	6060
Panel B: Treated Spot - Control Spot								
Event	-0.004	-0.018**	-0.02**	-0.003	0.023	0.026	0.018	-0.347
	(-1.368)	(-2.523)	(-2.194)	(-0.098)	(0.619)	(0.702)	(0.471)	(-0.888)
Treated	-0.016**	-0.074**	-0.08**	0.447**	0.453**	0.411**	0.368**	-2.303**
	(-2.558)	(-4.155)	(-3.896)	(5.2)	(5.46)	(4.897)	(4.33)	(-3.224)
Treated×Event	0.002	0.007	0.005	0.202**	0.193**	0.201**	0.217**	0.326
	(0.51)	(0.792)	(0.408)	(4.213)	(3.721)	(3.719)	(3.906)	(0.666)
Market cap	-0.003	-0.019	-0.024**	0.174**	0.16**	0.158**	0.154	-0.505
	(-0.752)	(-1.898)	(-2.084)	(2.263)	(2.114)	(2.05)	(1.952)	(-1.311)
Inverse Price	0.000	0	0.001	0.04**	0.042**	0.04**	0.038**	-0.029
	(0.543)	(-0.22)	(0.738)	(5.311)	(7.217)	(7.263)	(7.313)	(-0.789)
Market Vol	0.001**	0.004**	0.004**	-0.014**	-0.015**	-0.016**	-0.016**	0.141**
	(9.544)	(12.869)	(13.006)	(-10.408)	(-10.127)	(-9.768)	(-9.892)	(7.296)
Rollover	-0.002	-0.015**	-0.02**	0.1**	0.102**	0.1**	0.095**	-0.462
	(-1.827)	(-6.777)	(-5.632)	(6.808)	(5.735)	(5.29)	(4.749)	(-1.528)
Adjusted R^2	0.09	0.21	0.19	0.47	0.49	0.45	0.42	0.06
# of obs	6715	6713	6692	6715	6715	6715	6715	6715

5.2 Impact on liquidity

Tables 6 and 7 present the DiD estimates to analyse the impact of the OTR fee on liquidity of the treated SSF for Event 1 and 2 respectively. Both tables are organised as two panels, Panel A which shows the estimation results for various liquidity metrics for the impact of the fee on the treated SSF relative to the control spot. Panel B shows the estimation results for the same measures but for the impact of the fee on the treated spot relative to the control spot.

$\hat{\beta}_3$ is significant across all liquidity measures for the fee in Event 1 (Panel A, Table 6). The estimates are negative and statistically significant for the transactions cost measures. QSPREAD dropped by 5.8 basis points and the impact cost for lower and higher transaction sizes dropped by 3 and 4.6 basis points respectively. This shows that the fee in Event 1 led to a *decrease* in transactions costs in the treated SSF market relative to the control spot.

$\hat{\beta}_3$ is positive and significant for the depth measures. Depth improved by 14 to 15 percent at increasing depth in the order book. Finally, $\hat{\beta}_3$ is negative and significant coefficient for Amihud's illiquidity measure which indicates a reduction in the price impact of trades.

These 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).[28]

There is also some evidence of an indirect impact of the Event 1 fee on the liquidity of the treated securities. Panel B in Table 6 shows no significant impact on transactions costs of the Treated spot. But there is a positive impact on the depth of these stocks at all transaction sizes. These findings conclusively show that market liquidity of both the treated SSF and spot were impacted by the OTR fee in Event 1. This supports 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 of Hypothesis 3A where the alternative venue gains liquidity after an increase in the transactions cost due to the fee.

In contrast, there is little evidence showing that there was either a direct and indirect impact of the fee on market liquidity in Event 2. This is consistent with our finding that the Event 2 OTR fee did not have an impact on the aggregate OTR levels. Panel A in Table 7 shows the $\hat{\beta}_3$ is negative and significant for the QSPREAD which implies that the quoted spread of Treated SSF reduced relative to the Control spot. However, there is no similar improvement in any other measure of liquidity of SSF after the fee in Event 2. Even though we did find fewer orders being submitted in the higher price range of the limit order book, this does not show any impact on the depth of the SSF market. The lack of significant results for other liquidity measures leads us to conclude that there was

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

Table 7 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 × Event' ($\hat{\beta}_3$) is the interaction term that captures the causal effect of the fee on the OTR for the treated sample.
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}	top1depth	top5depth	top7depth	top10depth	illiq
Panel A: Treated SSF - Control spot								
Event	-0.005**	-0.029**	-0.034**	0.093	0.115**	0.124**	0.13**	-0.916**
	(-2.073)	(-3.879)	(-3.605)	(1.875)	(2.06)	(2.229)	(2.414)	(-2.511)
Treated	0.106**	-0.039**	-0.047**	2.119**	1.794**	1.752**	1.744**	-1.79**
	(8.238)	(-2.26)	(-2.052)	(16.757)	(13.982)	(13.551)	(13.558)	(-2.662)
Treated×Event	-0.041**	-0.009	-0.017	0.088	0.127	0.113	0.091	0.052
	(-3.132)	(-0.547)	(-0.838)	(0.975)	(1.312)	(1.163)	(0.955)	(0.088)
Market cap	-0.009	-0.023**	-0.024**	0.141**	0.12**	0.13**	0.134**	-0.728**
	(-1.927)	(-4.209)	(-3.51)	(3.417)	(2.149)	(2.21)	(2.244)	(-3.403)
Inverse Price	0.002**	0.002**	0.004**	0.027**	0.024**	0.022**	0.02**	0.07**
	(9.383)	(2.927)	(2.658)	(4.587)	(4.045)	(3.743)	(3.502)	(1.982)
Market Vol	0.001**	0.001**	0.001**	-0.003**	-0.004**	-0.003**	-0.003**	0.033**
	(5.54)	(5.995)	(4.335)	(-4.188)	(-4.493)	(-4.165)	(-4.039)	(2.454)
Rollover	-0.003	-0.005	-0.014	0.000	-0.015	-0.007	-0.014	-0.354
	(-1.538)	(-1.087)	(-1.519)	(-0.012)	(-0.4)	(-0.187)	(-0.407)	(-0.92)
Excluded	0.052**	0.038	0.057**	-0.25	-0.315**	-0.307	-0.266	1.248
	(2.832)	(1.72)	(1.983)	(-1.661)	(-1.993)	(-1.93)	(-1.726)	(1.337)
Adjusted R^2	0.54	0.31	0.3	0.76	0.67	0.65	0.65	0.11
# of obs	7485	7482	7408	7485	7485	7485	7485	7485
Panel B: Treated (Spot) - Control(Spot)								
Event	-0.006**	-0.026**	-0.03**	0.071	0.097	0.106	0.112**	-0.925**
	(-2.358)	(-3.421)	(-3.159)	(1.42)	(1.74)	(1.909)	(2.094)	(-2.528)
Treated	-0.003	-0.018	-0.001	0.347**	0.349**	0.352**	0.369**	-0.669
	(-0.615)	(-1.024)	(-0.022)	(3.05)	(2.837)	(2.799)	(2.908)	(-0.979)
Treated×Event	-0.005	-0.017	-0.03**	0.205**	0.185	0.193**	0.195**	-0.283
	(-1.5)	(-1.491)	(-1.995)	(2.295)	(1.901)	(1.975)	(2.021)	(-0.596)
Market cap	-0.003	-0.027**	-0.032**	0.207**	0.181**	0.188**	0.189**	-0.823**
	(-1.864)	(-4.748)	(-4.237)	(3.005)	(2.293)	(2.319)	(2.284)	(-4.048)
Inverse Price	0.002**	0.002**	0.004**	0.031**	0.027**	0.025**	0.023**	0.088**
	(17.458)	(3.446)	(3.17)	(5.945)	(5.054)	(4.689)	(4.341)	(2.755)
Market Vol	0.001**	0.002**	0.002**	-0.008**	-0.007**	-0.007**	-0.007**	0.031**
	(9.324)	(8.065)	(5.613)	(-6.401)	(-5.615)	(-5.464)	(-5.363)	(2.039)
Rollover	-0.001	-0.004	-0.007	0.010	-0.019	-0.012	-0.014	-0.436
	(-1.698)	(-1.326)	(-1.325)	(0.525)	(-0.786)	(-0.511)	(-0.626)	(-1.927)
Excluded	0.010	0.056**	0.069**	-0.385**	-0.398**	-0.424**	-0.449**	1.754**
	(1.867)	(2.934)	(2.76)	(-2.682)	(-2.509)	(-2.635)	(-2.781)	(2.248)
Adjusted R^2	0.66	0.34	0.32	0.45	0.35	0.32	0.3	0.13
# of obs	9515	9512	9435	9515	9515	9515	9515	9515

limited impact of the fee in Event 2 on market liquidity.

5.3 Impact on efficiency

Table 8 and 9 present the DiD estimations results on the impact of the fee of Event 1 and Event 2 on market efficiency measures. In these tables, Panel A presents the direct impact of the fee, while Panel B presents the results for the indirect impact.

$\hat{\beta}_3$ is significant for all efficiency measures in Panel A for Event 1. This suggests that the fee in Event 1 led to decreased levels of returns volatility and liquidity volatility for the Treated SSF relative to the Control spot. There is a positive and significant coefficient on $|VR-1|$ which suggests an improvement in information efficiency, at least over the shorter time intervals. Traders may be reluctant to aggressively place orders post the introduction of the fee. This could slow down the speed at which prices adjust to new information resulting in lower return volatility as well as higher variance ratios. Boehmer *et al.* (2020a) show that AT increases short-term volatility and improves price efficiency in a study of 42 international markets. Efforts to slow them down through OTR fee should therefore reduce volatility and worsen efficiency at least in the short term.

Interestingly, this decline seems to be not visible when we consider longer time intervals. For example, the coefficient on $|VR-1|$ becomes insignificant for variance ratios using time intervals greater than 30 minutes (See Table C.1 in the Apendix). This suggests that the fee could still be an effective regulatory tool to deter the harmful effects of high frequency trading. 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 8). The coefficients with the interaction term for all efficiency measures are insignificant. Thus, the results do not support Hypotheses 3A and 3B.

In Event 2, $\hat{\beta}_3$ is negative and significant for σ_r (Table 9). This implies that SSF returns volatility *decreased* after the fee was imposed. The source of this decline is not clear since orders at the best prices were not impacted by the fee. The results suggests a limited 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.

5.4 Channels that drive observed changes in liquidity in Event 1

In this section, we identify the traders who were behind the unproductive orders and how they were impacting liquidity supply. Table 10 presents the change in OTR using the DiD estimation for different trader categories around Event 1. Though the fee in Event 1 was implemented across all market participants on all their orders, we find that the biggest decline in OTR came in orders from non-institutional, non-proprietary (NINP) traders. As mentioned earlier, this category includes informal fund managers who contributed to a third of all algorithmic orders prior to the fee. This result is not surprising given that an

Table 8 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 $\times$ Event ($\hat{\beta}_3$)is the interaction term that captures the causal effect of the fee for the treated sample.
t-statistics based on standard errors clustered by stock and time are presented in parentheses. ** values indicate statistical significance at 5% level.

	σ_r	$\|VR-1\|$	LIQVOL$_{250k}$	LIQVOL$_{500k}$
Panel A: Treated (SSF) - Control (Spot)				
Event	0.111	-0.002	-0.003	0.005
	(0.458)	(-0.822)	(-0.472)	(0.464)
Treated	5.708**	-0.163**	-0.009	-0.015
	(5.826)	(-21.811)	(-0.449)	(-0.698)
Treated×Event	-3.507**	0.013**	-0.048**	-0.066**
	(-5.826)	(2.391)	(-4.067)	(-4.354)
Market cap	-1.042	0.006	-0.015	-0.012
	(-1.873)	(1.138)	(-1.451)	(-1.131)
Inverse Price	-0.031	0.001	-0.003**	-0.003**
	(-0.678)	(0.891)	(-2.767)	(-2.959)
Market Vol	0.227**	-0.001**	0.003**	0.003**
	(12.728)	(-6.866)	(8.711)	(8.219)
Rollover	0.041	-0.004	0.02**	0.018
	(1.327)	(-0.61)	(1.983)	(1.441)
Adjusted R^2	0.27	0.52	0.11	0.09
# of obs	6060	6060	6058	6034
Panel B: Treated (Spot)- Control (Spot)				
Event	-0.442	0.001	-0.006	0.002
	(-1.902)	(0.458)	(-0.809)	(0.214)
Treated	-1.937**	0.002	-0.042**	-0.051**
	(-3.304)	(0.622)	(-2.321)	(-2.577)
Treated×Event	0.168	-0.002	-0.007	-0.011
	(0.574)	(-0.512)	(-0.739)	(-0.823)
Market cap	-0.438	0.005	-0.013	-0.011
	(-1.254)	(1.857)	(-1.428)	(-1.124)
Inverse Price -0.006	0.002**	-0.002**	-0.003**	
	(-0.225)	(8.448)	(-2.664)	(-3.513)
Market Vol	0.131**	-0.001**	0.002**	0.003**
	(14.986)	(-7.004)	(8.293)	(8.055)
Rollover	-0.244**	0.005	-0.011**	-0.013**
	(-2.358)	(1.635)	(-2.976)	(-2.204)
Adjusted R^2	0.15	0.11	0.1	0.09
# of obs	6715	6715	6713	6689

Table 9 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 × Event ($\hat{\beta}_3$) is the interaction term that captures the causal effect of the fee for the treated sample.
t-statistics based on standard errors clustered by stock and time are presented in parentheses. ** values indicate statistical significance at 5% level.

	σ_r	$\lvert VR-1\rvert$	LIQVOL$_{250k}$	LIQVOL$_{500k}$
Panel A: Treated (SSF) - Control (Spot)				
Event	-0.534**	-0.001	-0.025**	-0.029**
	(-2.52)	(-0.382)	(-3.126)	(-2.337)
Treated	6.030**	-0.127**	-0.022	-0.025
	(6.195)	(-17.487)	(-1.317)	(-1.186)
Treated×Event	-2.844**	0.011	-0.001	-0.009
	(-2.956)	(1.404)	(-0.112)	(-0.57)
Market cap	-0.719**	0.014**	-0.008	-0.005
	(-2.09)	(3.347)	(-1.441)	(-0.7)
Inverse Price	0.137**	0.002**	0.001	0.001
	(8.444)	(9.39)	(1.255)	(1.19)
Market Vol	0.042**	0.000	0.001**	0.001**
	(3.942)	(-0.152)	(3.49)	(2.062)
Rollover	-0.176	-0.006	0.008	-0.008
	(-0.793)	(-1.372)	(1.36)	(-1.127)
Excluded	3.813**	-0.01	0.043**	0.06**
	(2.885)	(-0.95)	(2.449)	(3.113)
Adjusted R^2	0.44	0.38	0.08	0.03
# of obs	7485	7485	7482	7388
Panel B: Treated (Spot) - Control (Spot)				
Event	-0.526**	-0.002	-0.024**	-0.026**
	(-2.547)	(-0.466)	(-2.937)	(-2.151)
Treated	-0.820**	0.010	-0.02	-0.012
	(-2.133)	(1.854)	(-1.271)	(-0.582)
Treated×Event	-0.368	0.011**	-0.005	-0.012
	(-1.231)	(2.094)	(-0.465)	(-0.758)
Market cap	-0.364**	0.008**	-0.006	-0.004
	(-2.26)	(3.763)	(-1.311)	(-0.719)
Inverse Price	0.143**	0.002**	0.001	0
	(12.402)	(12.67)	(1.601)	(0.881)
Market Vol	0.053**	0.000	0.001**	0.001**
	(7.537)	(-0.992)	(5.677)	(2.918)
Rollover	-0.149	-0.01**	0.002	-0.003
	(-1.448)	(-3.107)	(0.529)	(-0.595)
Excluded	1.167**	-0.024**	0.053**	0.076**
	(2.485)	(-2.98)	(3.395)	(3.335)
Adjusted R^2	0.58	0.2	0.09	0.03
# of obs	9515	9515	9512	9415

OTR fee would be most binding for traders who are less likely to be informed. Interestingly, we do find that both NINP and PROP orders shift some of their derivatives order activity to the underlying stock market which did not have the fee.

Table 10 DiD estimates of the impact of the fee on OTR by 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. The dependent variable is the stock-day value-weighted average of the OTR across orders. 'Treated × Event' is the interaction term that captures the causal effect ($\hat{\beta}_3$) of the fee on the OTR for the treated stocks.
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}
Event	0.137	0.121	0.081	0.036	0.05	0.045
	(0.935)	(1.879)	(0.195)	(1.952)	(1.072)	(0.678)
Treated	17.784**	4.116**	42.979**	0.2**	0.026	0.283
	(15.632)	(11.682)	(14.996)	(3.308)	(0.446)	(1.517)
Treated×Event	-4.605**	-0.723	-3.092	0.13**	-0.051	0.926**
	(-4.936)	(-1.837)	(-1.184)	(3.657)	(-0.986)	(4.78)
Market cap	-0.857	-0.191	0.013	-0.011	-0.031	0.301
	(-1.633)	(-1.139)	(0.007)	(-0.413)	(-1.216)	(1.247)
Inverse Price	0.136	-0.003	-0.015	-0.012**	-0.008	-0.061**
	(1.922)	(-0.158)	(-0.096)	(-3.332)	(-1.958)	(-4.376)
Market Vol	-0.025	0.007	-0.015	-0.003**	-0.001	-0.009**
	(-1.163)	(0.855)	(-0.293)	(-3.641)	(-0.445)	(-2.744)
Rollover	3.997**	0.591	13.311**	0.013	0.007	0.006
	(3.692)	(1.795)	(4.029)	(0.639)	(0.214)	(0.134)
Adjusted R^2	0.51	0.18	0.53	0.18	0.01	0.25
# of obs	6060	5253	6060	6715	6194	6715

While our results show that curbing these unproductive orders improved liquidity supply, it does not establish the channel through which these orders impacted the incentives of those who offer liquidity. In order to do this, we explore two specific channels – adverse selection and inventory management – mentioned in the following literature.

Biais and Woolley (2012) describe "stuffing" as placement of a high number of unwieldy orders generating congestion and impairing market access for other traders. Most literature have attributed this activity to HFT traders who are able to obtain and trade on information faster than others. Hoffmann (2014) shows that the presence of HFT traders makes other traders strategically submit limit orders with lower execution probability. Biais *et al.* (2015) suggest that fast traders induce adverse selection for others because of their ability to realise the benefit of their private information faster. Yeushen (2021) shows that queuing uncertainty for limit orders could result in short-run overshooting of orders and subsequent cancellation even with no specific informational advantage for these traders. In fact, he attributes adverse selection (the threat of being picked off) to be the main trigger for limit orders to get cancelled and repriced. Empirical papers such as Brogaard *et al.* (2015) confirm these theoretical predictions that faster traders indeed do impose higher adverse selection on slower traders.

Ait-Sahalia and Saglam (2016) show that fast traders could impact the management of inventory for slower liquidity suppliers. They model the trade-off between the spread revenue and the inventory cost for a market maker and show that the relative speed of the market maker vis a vis others could determine how competitive they are in offering liquidity.

Brogaard *et al.* (2015) test the impact of these channels on liquidity suppliers following an optional colocation upgrade at NASDAQ OMX Stockholm. They find that the upgrade was predominantly taken up by market makers suggesting that they are the ones seeking a speed advantage over other traders. Though there are no designated market makers at the NSE, we follow the same approach to determine the impact of order stuffing on liquidity suppliers. In particular, we look at whether adverse selection costs and returns for taking inventory risk change significantly for passive orders after the introduction of OTR fee.

We measure adverse selection costs as the signed difference between the mid-quote 5 minutes after the trade and the prevailing mid-quote (signed such that the measure is positive for buyer-initiated trades and vice-versa). An increase in this measure would suggest an increase in adverse selection cost for the trader who offered liquidity in this trade. Similarly, we measure the return from taking inventory risk through realised spreads for passive orders. Realised spread is defined as the signed difference between the trade price and the mid-quote 5 minutes after the trade (signed such that the measure is positive for buyer-initiated trades and vice-versa). It captures the revenue for a liquidity supplier net of adverse selection cost and is meant to compensate her for the inventory risk and order processing costs. A decrease in the realised spread for passive orders would suggest a decrease in their return for taking on the inventory risk.

We use the DiD estimation described earlier using value-weighted stock-day averages across passive orders for these measures as our dependent variable. We estimate for the full sample as well as for different trader categories for the two events separately. Table 11 provides the results of our estimations.

The results show that adverse selection costs decline significantly for the full sample as well as for the liquidity suppliers within PROP and NINP categories. The value of $\hat{\beta}_3$ in Table 11 shows that the decline is about 180 bps overall, with 310 bps for PROP and 170 for NINP traders offering liquidity. This suggests that the adverse selection costs declined more for the PROP traders relative to the NINP traders. The return for taking inventory risk, however, does not change much suggesting that changes in profitability to liquidity suppliers came entirely from reduced adverse selection and not through better inventory management.

We conjecture, therefore, that the unproductive orders which were congesting the order

Table 11 DiD estimations of the impact of the fee on channels for orders by trader categories, Event 1

The table presents the DiD estimation results for how realised spreads and adverse selection costs change for the Treated (SSF) market relative to the Treated Spot after the OTR fee was imposed. Realised spread is measured as the difference between the trade price and the mid-quote 5 minutes after the trade (signed such that the measure is positive for buyer-initiated trades and vice-versa). Adverse selection costs is the signed difference between the mid-quote 5 minutes after the trade and the prevailing mid-quote. We measure these costs for the passive trader behind the trade (one provides liquidity to the initiator of the trade). All measures are stock-day value-weighted averages across orders. For this table, the estimated coefficient on *Inverse Price* has been scaled up by 100 for reporting purposes.
t-statistics based on standard errors clustered by stock and time are presented in parentheses. ** values indicate statistical significance at 5% level.

	Realised spread				Adverse selection cost			
	All	INST	PROP	NINP	All	INST	PROP	NINP
Event	-0.001	-0.01	-0.004	-0.003	-0.006	0	0.005	-0.004
	(-0.285)	(-0.895)	(-1.172)	(-0.894)	(-1.507)	(0.05)	(1.339)	(-0.977)
Treated	-0.028**	-0.057**	-0.027**	-0.028**	0.039**	0.054**	0.058**	0.033**
	(-5.233)	(-4.297)	(-4.862)	(-5.267)	(4.519)	(4.119)	(7.056)	(3.815)
Treated×Event	-0.004	0.006	-0.003	-0.004	-0.018**	-0.01	-0.031**	-0.017**
	(-0.843)	(0.404)	(-0.516)	(-0.802)	(-2.837)	(-0.706)	(-4.447)	(-2.907)
Market cap	-0.002	-0.014**	-0.001	-0.002	-0.009**	0.008	-0.008**	-0.008**
	(-0.547)	(-3.08)	(-0.464)	(-0.514)	(-2.294)	(1.442)	(-2.102)	(-2.106)
Inverse Price	-0.006	0.009	-0.048**	0.015	-0.016	0.006	0.009	-0.030
	(-0.297)	(0.166)	(-2.134)	(0.679)	(-0.45)	(0.095)	(0.266)	(-0.79)
Market Vol	0.000	0.001	0.000	0.000**	0.003**	0.000	0.003**	0.003**
	(-0.766)	(1.484)	(0.21)	(-2.158)	(14.503)	(0.538)	(10.288)	(17.163)
Rollover	-0.011	0.002	0.005	-0.016**	0.007	0.007	-0.004	0.01
	(-1.871)	(0.116)	(0.849)	(-2.85)	(1.427)	(0.323)	(-0.809)	(1.66)
Adjusted R^2	0.05	0.02	0.03	0.05	0.12	0.01	0.11	0.12
# of obs	6013	4609	5982	6013	6013	4609	5982	6013

book imposed adverse selection on genuine liquidity suppliers in the market. Levying a fee on them helped mitigate the cost for liquidity suppliers and improve liquidity in the market. Not only do we find liquidity suppliers tightening spreads and improving depth, but we also find that orders of proprietary and institutional traders stay in the market for a longer time (see Table 12).

Table 12 DiD estimations of the impact of the fee on Time in the system for orders by trader categories, Event 1

The table presents the DiD estimation results for the effect of the OTR fee on the time that orders spend in the market for Treated SSF and Treated Spot. Time in the system is defined as the time (in secs) from the first entry to the last message for an order. The dependent variable is the logarithm of the stock-day value-weighted average for the time in the system for orders. The regressions are run separately for orders placed by INST, PROP and NINP traders.
t-statistics based on standard errors clustered by stock and time are presented in parentheses. ** values indicate statistical significance at 5% level.

	INST	PROP	NINP
Event	0.05	-0.27**	0.05**
	(0.38)	(-3.91)	(2.20)
Treated	-0.90**	-2.05**	-0.98**
	(-5.59)	(17.63)	(-14.97)
Treated×Event	1.31**	0.28**	-0.03
	(6.69)	(3.04)	(-0.55)
Log(Marketcap)	0.18**	0.02	0.03
	(2.44)	(0.27)	(0.93)
Inverse Price	0.00	0.02**	0.01**
	(0.01)	(1.91)	(3.61)
Rollover date	0.02	-0.10**	-0.03
	(0.13)	(-2.09)	(-1.44)
Market vol	-0.01	-0.01**	-0.01**
	(-1.15)	(-2.44)	(-7.18)
Adjusted R^2	0.06	0.64	0.64
# of Obs	5,208	6,013	6,013

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 penalise 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. This is unlike the fragmented markets seen in the U.S. and so the impact can be measured in a statistically robust manner. Moreover, the fee was introduced in the single stock derivatives market while the underlying cash market for the stocks was left untouched.

This interesting microstructure setting allows us to study the impact of the fee on OTR levels, market liquidity and efficiency using a differences-in-differences regression approach on two innovative sets of treated and control securities. The first set compares single stock futures subject to the fee with a group of control stocks that do not have futures traded on them but are similar in every other way. To determine whether traders shifted activity from the futures to the cash market after the fee, we also construct another comparison set within the cash market alone whereby we compare trading in stocks that are subject to a fee (in their futures market) with a group of similar stocks that do not have futures traded on them.

The data that we use is also unique compared to similar trades and quotes 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 an order from other market participants. The last category is a catch-all category that includes retail traders. This allows us to identify whether all traders or only some categories of traders were taxing the system using unproductive orders. Moreover, we are able to identify the active and the passive trader behind each trade allowing us to examine the impact of these unproductive orders on liquidity suppliers.

We find that when the exchange used the OTR fee on all traders 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 percent price limit (applied on last traded price), there was no impact on aggregate OTR and on most measures of market liquidity and efficiency. 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 insights to understanding the mixed results recorded by earlier literature on the impact of such interventions. Furthermore, we find that the unproductive orders that were congesting the order book imposed adverse selection costs on traders offering liquidity in the market. Levying a fee on them helped reduce this cost, allowing traders to improve liquidity in the market.

Our study has important policy implications for regulators and exchanges who want to penalize traders managing their orders aggressively through frequent cancellations. While order stuffing does impose a cost on the infrastructure, efforts to curb it through a fee or other methods require deeper understanding of who sends these unproductive orders and how they may impact the incentives of other liquidity suppliers in the market.

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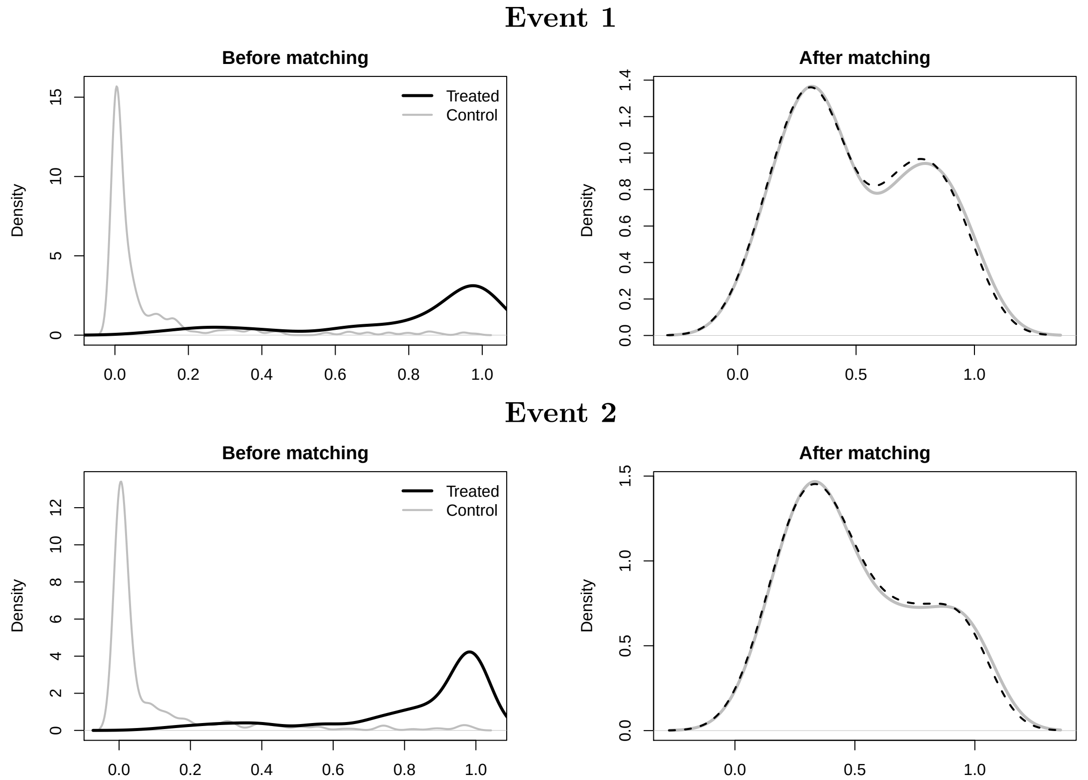
Appendix A Creating an optimal control sample

In this section, we present the details of the sample of stocks that were used to identify the optimal control for the treated SSF. Figure A.1 presents the empirical 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 an overlap in the density curves of the final sample for each of the events.

Figure A.1 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.



The region of common support for the treatment and control firms is very small primarily because not all stocks listed on the NSE trade on the derivatives market. The number of stocks is limited based on certain thresholds defined in terms of market cap and liquidity. This group includes mostly the top 200 stocks that would meet the criteria. In matching the treated firms (derivative stocks) with the comparison group firms (non-derivative stocks), it is unlikely that we will find a match for the top 100 stocks. Hence the sample size essentially reduces to the remaining 100 stocks that met the derivatives criteria, and the control firms that missed the threshold just by a small amount.

Table A.1 reports the match balance statistics for each event and for all matching covariates

Table A.1 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	0.010	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

between the treated and control firms in the final sample in the pre-intervention period. After matching, we observe that there are no significant differences in the mean values of the covariates for the treated and control group.

Appendix B Parallel trends assumption

Figure B.1 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.

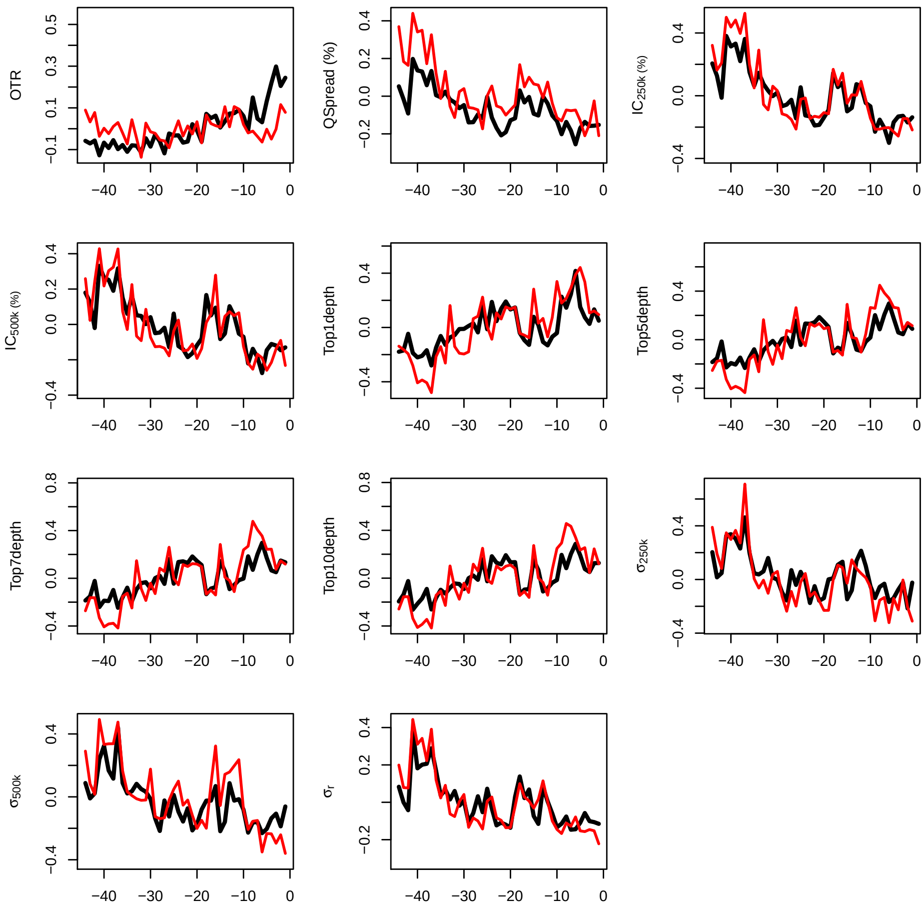
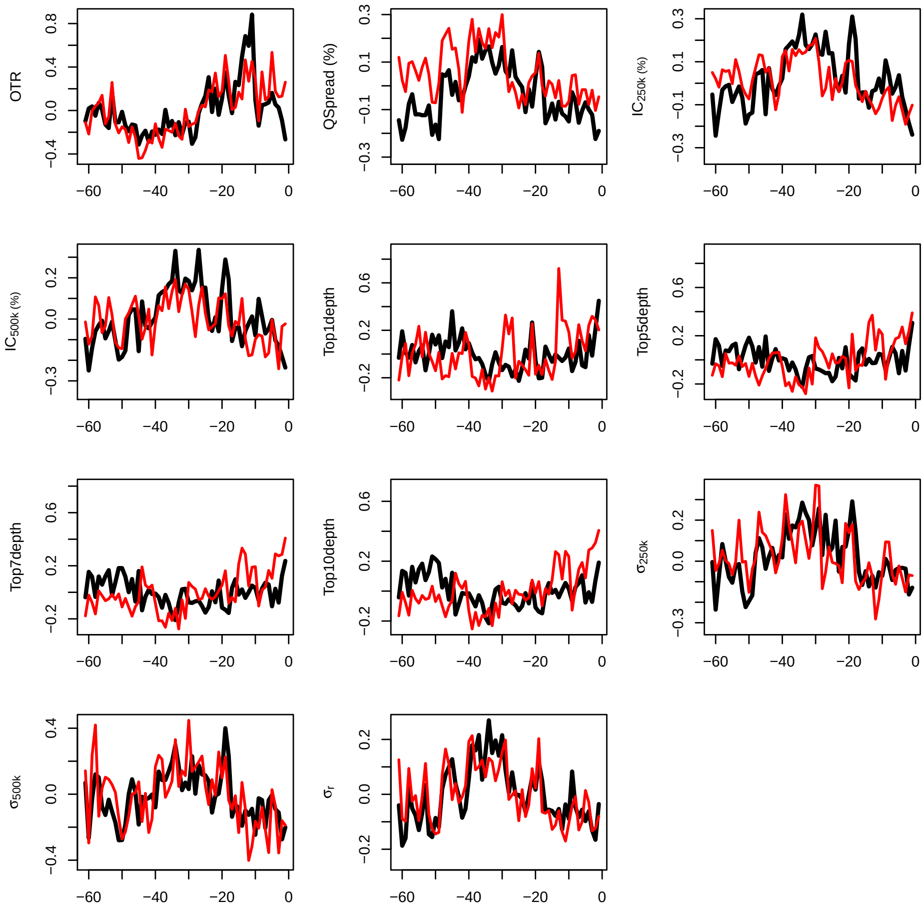


Figure B.2 Pre-treatment outcome variables for matched treated and control stocks on the spot market around Event 2

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.



Appendix C DiD regression results for variance ratio tests beyond 30 minutes

Table C.1 DiD estimation results for impact on variance ratio beyond 30 minutes

The table presents the DiD estimation results for variance ratio over horizon beyond 30 minutes. $|VR-1|_{35min}$ represents variance ratio computed using 35 minute returns to 5 minute returns. Similarly, $|VR-1|_{60min}$ shows the ratio computed using 60 minute returns to 5 minutes. The results are reported for the treated SSF versus the control spot. 'Treated × Event is the interaction term that captures the causal effect of the fee for the treated sample.
t-statistics based on standard errors clustered by stock and time are presented in parentheses. ** values indicate statistical significance at 5% level.

	$\|VR-1\|_{40min}$	$\|VR-1\|_{45min}$	$\|VR-1\|_{50min}$	$\|VR-1\|_{55min}$	$\|VR-1\|_{60min}$
Event	-0.005	-0.005	-0.005	-0.006	-0.007
	(-1.208)	(-1.155)	(-1.236)	(-1.463)	(-1.54)
Treated	-0.316**	-0.325**	-0.331**	-0.334**	-0.335**
	(-25.771)	(-25.114)	(-24.924)	(-24.584)	(-24.453)
Treated×Event	0.012	0.009	0.007	0.005	0.002
	(1.298)	(0.879)	(0.64)	(0.448)	(0.206)
Market cap	0.012	0.012	0.012	0.012	0.012
	(1.199)	(1.164)	(1.155)	(1.171)	(1.165)
Inverse Price	0	0	0	0.001	0.001
	(0.449)	(0.413)	(0.448)	(0.551)	(0.62)
Market Vol	-0.002**	-0.002**	-0.002**	-0.002**	-0.002**
	(-6.338)	(-6.409)	(-6.306)	(-6.418)	(-6.608)
Rollover	-0.003	-0.003	-0.002	-0.002	0
	(-0.351)	(-0.371)	(-0.278)	(-0.226)	(-0.041)
Adjusted R^2	0.66	0.65	0.65	0.64	0.64
# of obs	4218	4218	4218	4218	4218