

When is the Order to Trade Ratio fee effective?

Nidhi Aggarwal* Venkatesh Panchapagesan Susan Thomas

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.

JEL codes: G14, G18

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

*Nidhi Aggarwal is at the Indian Institute of Management, Udaipur. Email: nidhi.aggarwal@iimu.ac.in Venkatesh Panchapagesan is at the Indian Institute of Management, Bangalore. Email: venky@iimb.ac.in and Susan Thomas is at xKDR Forum and Jindal Global Business School Email: stthomas.entp@gmail.com We acknowledge the support of the NSE-NYU Stern School of Business Initiative for the Study of Indian Capital Markets. We thank Gideon Saar and an anonymous referee for their comments and suggestions. We thank the NSE for the use of underlying data, Nanda Kumar at NSE and officials from SEBI for in-depth discussions, Karan Sehgal for research assistance, Chirag Anand for technological assistance and Yakov Amihud, Jonathan Brogaard, Sugato Chakravarty, R L Shankar, and Pradeep Yadav for their comments and suggestions at various stages and drafts of the paper. The paper has also benefitted from discussions with the participants at the NSE-NYU Indian Financial Markets Conference 2014, 5th Emerging Markets Finance conference, 2014, the 4th Conference on The Industrial Organisation of Securities and Derivatives Markets: High Frequency Trading, 2015, the IGIDR-NSE field workshop on financial securities markets, 2017, at International Conference on Market Design and Regulation in the Presence of High-Frequency Trading, Hong Kong, 2017, 11th Financial Risks International Forum, 2018, and the IIM Calcutta-NYU Stern India Research Conference in Financial Economics at NYU Stern, 2019. An earlier version of the paper was titled “Do regulatory hurdles on algorithmic trading work?”. The findings and opinions presented in this paper are those of the authors and not of their employers or NSE or NYU. All errors remain our own.

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).

But high levels of trading activity has also been a source of heightened concern, leading regulators and exchanges to propose interventions to reduce 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 on such interventions document that they have an adverse effect. For example, when the Scandinavian countries imposed a transactions tax on equity trading in the 1980’s, local trading 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 market 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) was the first exchange to use this fee in 2005.³ Since then, more exchanges have used the OTR fee to slow down high frequency trading. These include the Italian Stock Exchange, Toronto

¹The 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.

²Anderson *et al.* (2021) 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.

³See <https://www.mypivots.com/board/topic/217/1/cme-cancellation-fees>.

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 a deterioration in market liquidity after the fee was imposed (Malinova *et al.*, 2018; Friederich and Payne, 2015; Capelle-Blancard, 2017). In contrast, Jorgensen *et al.* (2018) find that after an OTR fee was imposed at the Oslo Stock Exchange, the level of orders to trades dropped without any adverse impact on market quality. They conclude that this was because the fee was designed to exempt 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 of India (NSE). The objective to impose the fee was different across the two implementations. 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 after algorithmic trading was well established, and the regulator introduced the fee among heightened public policy concerns that algorithmic trading leads to excessive trading activity.

Since the objectives were different, the design of the fee also varied across the two implementations. The first fee applied *uniformly* on all participants and all orders. 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. The two implementations were similar in that, the fee was imposed only on equity derivatives in both instances. There was no fee on orders placed in the spot market. These differences and similarities 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.⁴ Of these, the third category is a catch-all category that includes a variety of informal fund managers, along with retail traders. These features 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 the OTR level and quality of the market.

Several other features in this 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 consolidated 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

⁴Institutions 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.

venue (the Bombay Stock Exchange) would come at a significant loss of liquidity.⁵

We use a difference-in-difference regression framework to understand the casual impact of the OTR fee. Since the fee was only imposed on SSF trading, an obvious control is the underlying stock. But 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 on 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).

In order to overcome this problem, we create a separate control group by exploiting a second feature of the Indian markets: not all stocks have derivatives traded on the exchange. To be eligible for derivatives trading, a stock is required to meet a well-defined minimum criteria. We use this criteria to identify a control group of stocks (without futures trading) which are *matched* to the (treated) stocks with futures trading.

We can then assess the 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, and the indirect impact of the fee by comparing the *matched* treated stocks on the spot market with the *matched* control stocks on the spot market.

Our analysis of the direct impact of the OTR fee shows that when the exchange implemented the fee to disincentivise traders from excessive loading on the trading system, it led to lower aggregate OTR on the SSF market. But the reduction in the OTR did not lead to lower market liquidity. This is contrary to the results obtained in other studies (Friederich and Payne, 2015; Malinova *et al.*, 2018). In fact, we find an *improvement in liquidity* after the fee. We find a loss of short-term efficiency (measured by the variance ratio of short-term returns), an effect which dissipates over longer intervals.

We argue that the improvement in market liquidity came from a reduction in excessive order activity which imposed high cost on liquidity suppliers. In particular, we find a significant decline in the OTR of non-institutional-non-proprietary traders. This category of traders included private fund managers who generated a third of all algorithmic orders in the sample.

We then carry out a closer examination of two channels, through which imposing a fee on excessive order activity affects the incentives of liquidity suppliers – the costs of adverse selection and managing inventory. Traders who can place orders or cancel orders faster, reduce (increase) the chance of slower liquidity suppliers trading during favourable (adverse) market conditions. If fast traders are picking off slower liquidity suppliers using marketable orders, they are likely to have a low OTR and will not be affected by the OTR fee. But, if fast traders who supply liquidity are cancelling frequently to protect themselves, then they are reducing their own adverse selection but exacerbating adverse selection for slower

⁵When costs of trading increases on one venue, trading shifts to alternative venues (Brunnermeier and Pedersen, 2009; Aggarwal and Thomas, 2019).

liquidity suppliers. These fast traders are likely to have high OTR and will be impacted by the OTR fee. Similarly, the inability to predict executions because of rapid order placement and modification by fast traders could lead slower liquidity suppliers to carry unwanted inventory risk and hence quote wider spreads. In other words, fast liquidity suppliers exacerbate the adverse selection and inventory management costs for slow liquidity suppliers. A fee on OTR, while hurting fast liquidity suppliers, could benefit slow liquidity suppliers.

We use the approach in Brogaard *et al.* (2015) and find a significant reduction in the adverse selection cost (about 180 bps) for liquidity suppliers after the imposition of the fee. The reduction is visible for both proprietary and non-institutional-non-proprietary traders, suggesting that the benefit to slower liquidity suppliers outweighed the cost to faster liquidity suppliers within these categories. 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. We do not see any change in the revenues of managing inventory for liquidity suppliers driven by the fee suggesting that excessive order activity was hurting liquidity suppliers mainly by exacerbating their adverse selection cost.

Our analysis of the indirect effects of the OTR fee shows 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.

Our analysis of the second implementation of the OTR fee by the regulator find that it had no impact on the aggregate OTR level. 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-

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, with much of the evidence from the markets in Canada, the U.S. 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 6th 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 excessive order submissions by AT and HFT that do not always convert into trades (Hagstromer and Norden, 2013). Such orders are not seen as providing genuine liquidity but instead only imposing a cost on market infrastructure. Fabozzi *et al.* (2011) contend that the need to constantly upgrade exchange infrastructure could increase the cost of trading that is not captured in many HFT studies.⁸ Though academic research

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.

⁸In India, anecdote suggests that the regulator required exchanges to maintain capacity to meet at least

has not found major evidence on market manipulation, regulators have often used this reason to motivate interventions to slow down AT and HFT. For example, the head of the Italian securities regulator (CONSOB), as a rationale to slow down HFT, stated that “the ability of high frequency traders to suddenly cancel orders placed before they are executed, displacing other investors, can generate a misleading representation of the actual depth of the order book, creating favourable conditions for market manipulation.” (Friederich and Payne, 2015).

Two interventions that are most widely implemented to slow down AT and HFT are 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 “excessive” 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 on market quality 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 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 also do not find any benefits from the fee either.

Such mixed evidence raises questions about the conditions under which the fee achieves its intended objective and when it fails to deliver. In the next section, we discuss the possible channels through which such a fee can be effective.

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 excessive order activity in the market. 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, they will change their trading

twice the maximum load on its infrastructure at any time.

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. Or 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 with excessive order activity, then the fee will lead to *lower* aggregate OTR levels.

Apart from imposing a cost on infrastructure, excessive order activity, and efforts to reduce them through a OTR fee, could impact market quality as well. Previous literature has shown two ways that fast traders impact adverse selection and inventory management of slower liquidity suppliers. First, fast traders can use speed to pick off stale quotes of liquidity suppliers (examples include Biais *et al.* (2015), Foucault *et al.* (2016a) and Foucault *et al.* (2016b)). This requires use of marketable orders that, by design, have low OTR (closer to 1).⁹ An OTR fee would, therefore, have little effect on this strategy.

Second, fast traders can cancel their own quotes before others can pick them off (examples include Hoffmann (2014), Jovanovic and Menkveld (2016), Foucault and Moinas (2018), and Baldauf and Mollner (2021)). This would mean frequent cancellation and repricing of quotes if such fast traders are market makers. Hagstromer and Norden (2013) document that market making orders constitute a large part of HFT orders. Moreover, Brogaard *et al.* (2015) show that traders who invest in speed like co-location services are primarily market makers. Fast market makers will have high OTR and would be impacted by the new OTR fee.¹⁰

While aggressive order management reduces adverse selection for fast market makers, it increases the adverse selection risk for slower liquidity suppliers. Several studies highlight this differential impact.¹¹ Hoffmann (2014) shows that when fast traders are picked off less frequently, it directly translates to a more severe winners' curse problem for slow traders. An OTR fee that penalises excessive order management will have the opposite

⁹Budish *et al.* (2015) suggest that even "stale quote snipers" need to cancel their orders whenever their attempt to snipe does not work out.

¹⁰Foucault and Moinas (2018) point out that "...a race between traders attempting to lift stale quotes before they are cancelled and liquidity providers attempting to cancel quotes before they are picked off. This race is one reason why cancellations-to-trade ratios have considerably increased in recent years..."

¹¹In the words of Hendershott *et al.* (2011), "If some users of AT (*algorithmic trading*) are better at avoiding being picked off, they can impose adverse selection costs on other liquidity suppliers as in Rock (1990) and even drive out other liquidity suppliers" (phrase in *italics* added by us). Similarly, Baldauf and Mollner (2021) argue that "...faster liquidity providers are better able to cancel their mispriced quotes when information arrives, which shifts the adverse selection burden onto their slower counterparts—or, in the language of the industry, leaves them to be "overrun.""

effect. Whether adverse selection for the market as a whole declines or increases will depend on the relative impact of the fee on fast and slow liquidity suppliers in the market, and remains an empirical question (Foucault and Moinas, 2018).

The effect of speed on inventory management by market makers is explored in Ait-Sahalia and Saglam (2017). They show that timely cancellations and re-entry allows fast market makers to lower their cost of holding inventory. This allows these fast market makers to make markets more competitively and to improve liquidity, but at the expense of a high OTR. Ait-Sahalia and Saglam (2017) show that a fee on cancellations worsens market liquidity when it is most needed.

Lower market liquidity could negatively impact price efficiency through an adverse impact on the profitability of informed traders and vice-versa (Bloomfield *et al.*, 2009). Brogaard *et al.* (2014) show that fast traders facilitate price efficiency and attempts to slow them through a fee could hurt efficiency. The effect of an OTR fee on liquidity and efficiency will finally depend on whether it adversely impacts fast liquidity suppliers more than it benefits the slower liquidity suppliers.

These arguments lead to the following two competing hypotheses:

Hypothesis 2A: If the benefits to slower liquidity suppliers outweigh the detrimental impact on faster liquidity suppliers, then liquidity and price efficiency will improve after the fee imposition.

Hypothesis 2B: If the benefits to slower liquidity suppliers are lower than the detrimental impact on faster liquidity suppliers, then 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:

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.

We now present the context and the data with which we test these hypotheses.

3 Indian equity markets and OTR fee regimes

Our analysis uses the microstructure features of, 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 India¹² 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, NSE was the world’s largest derivatives exchange by volume.¹³ The single stock options volumes have started rising only in recent years, contrary to the trends in the U.S equity markets where single stock options trading dominate equity derivatives trading activity.¹⁴

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 and closing prices being 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. Derivatives includes futures and options on single stocks, and on indices, but these trade only on 166 stocks.¹⁵ 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 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

¹²The other securities exchange is the Bombay Stock Exchange, BSE.

¹³*India now has world’s largest derivatives exchange by volume*, Bloomberg, January 21, 2020.

¹⁴In India, most of the options volumes are concentrated on Nifty index options.

¹⁵Data as of May 2019.

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 from 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.¹⁶ A year later, NSE issued a circular in June 2010 observing that there was a ‘notable’ reduction in the OTR in the derivatives segment. The exchange then reduced the OTR fee as well as raised the minimum thresholds for daily OTR.¹⁷

By 2012, AT on Indian equity had increased to significant levels.¹⁸ Concerned about the rising AT levels, SEBI directed the exchanges to impose an OTR fee on derivatives trading, in a circular in 2012, stating:¹⁹

“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 in having several additional exemptions. For example, it was applicable *only* on algorithmic orders. 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.²⁰ The reason stated for 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 OTR fee in May 2013, when SEBI directed exchanges to double the magnitude of the fee (SEBI, 2013). Table 1 summarises the details of the OTR fee implementation across different episodes.

Figure 1 presents a graph with vertical lines that mark various implementations of an OTR fee, superimposed on the fraction of the SSF trading volume at the NSE which was due to AT. 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

¹⁶In implementation, this fee structure was similar to the OTR fee structure at the Italian Stock Exchange, Borsa Italiana in 2012 (Friederich and Payne, 2015).

¹⁷See NSE (2010).

¹⁸Aggarwal and Thomas (2014) shows that the level of AT increased from 20 percent in 2010 to 55-60 percent in 2013.

¹⁹See SEBI (2012a)

²⁰In 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.

Table 1 Details of the OTR fee implementation

2009-10	2012-13
• By the exchange on equity derivatives • on all participants • on all order types	• By the regulator on equity derivatives • <i>not applicable</i> to participants who are market makers • <i>only</i> on algo orders • <i>only</i> on orders <i>outside</i> $\pm 1\%$ 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.

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 impact of the OTR fee 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:²¹

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

- a) Pre event period: July 2009 to September 2009
- b) Post event period: October 2009 to December 2009

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

- a) Pre event period: April 2012 to June 2012
- b) Post event period: July 2012 to September 2012

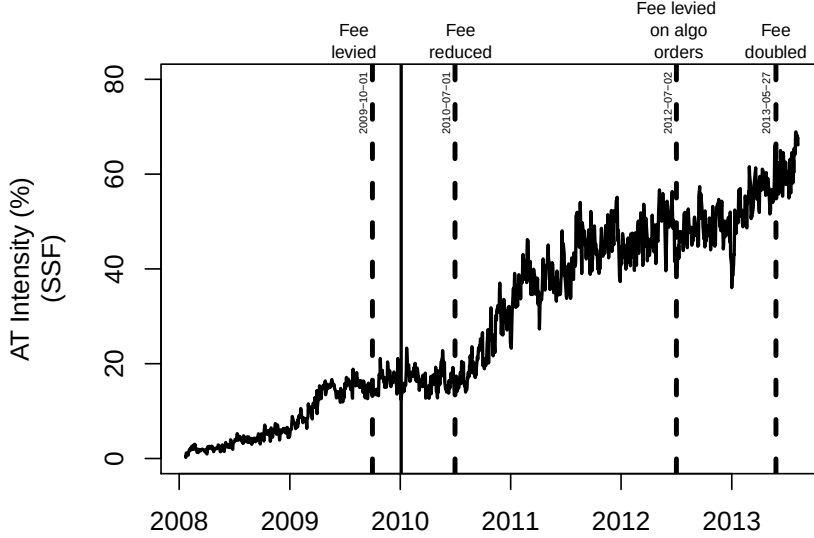
We use proprietary, tick-by-tick orders and trades (TAO) data for the equity spot and the SSF segments of NSE during our sample periods.²² Each trade and order is time-stamped

²¹We 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.

²²Other studies using this data include Nawn and Banerjee (2018), Chakrabarty *et al.* (2019), Nawn and Banerjee (2019).

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.



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,²³ and a trader type indicator of ‘custodian’, ‘proprietary’ and ‘non custodian non proprietary’. The trader category ‘custodians’ includes 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 these categorisations do not lead to a clean separation between who uses algorithms and who does not: each category

²³In India, each trader using an algorithm is required to register herself as an algorithmic trader with 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.

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).²⁴ 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 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.²⁵

²⁴These 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.

²⁵A choice in testing for market efficiency with high frequency data is whether it is more appropriate to use traded prices or quotes in calculating variance ratios. The traditional analytical framework of testing market efficiency is based on the behaviour of traded prices which include the bid-ask bounce. This suggests

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 is that because AT and HFT orders are withdrawn before another trader can act upon it, 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 increase expected returns of the underlying stocks. In order 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 the 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 allows us to compare 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). This approach 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.

that the variance ratio using quotes might be a less noisy estimate of market efficiency. However, there is mounting evidence that high frequency trading triggers volatility in the quotes themselves (Chakrabarty and Tyurin, 2011; Baruch and Glosten, 2013; Hasbrouck, 2018). In the face of these arguments, we use traded prices in calculating VR to test for price discovery and market efficiency, similar to Leone and Kwabi (2019) and Benos and Sagade (2016).

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

We identify an alternate control group as those stocks that are close to, but do not meet, 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’²⁶ 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.²⁷ In particular, we use market capitalisation (‘market cap’), prices, floating stock, turnover and number of trades.²⁸ The covariate values are calculated as the average values for the period before the fee was announced.

In order to capture multiple covariates in one dimension, we use propensity score matching 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.²⁹ Details of the matching exercise are presented in Section A of the Appendix.

²⁶This is the trade quantity that can cause a price movement of quarter sigma.

²⁷We remove stocks that underwent any corporate action including stock split, merger, rights and bonus issue or a buyback during the periods of our analysis.

²⁸Using 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.

²⁹This 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.

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 sample statistics for market quality of the matched samples during the pre-event period for both Event 1 and Event 2. ‘Treated SSF’ represents the set of matched treated stocks (derivatives that were directly affected by the fee). ‘Treated spot’ represents the stocks traded on the spot market underlying the SSF 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 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.³⁰ 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:

$$\text{MEASURE}_{i,t} = \alpha + \beta_1 \times \text{TREATED}_i + \beta_2 \times \text{EVENT}_t + \beta_3 \times \text{TREATED}_i \times \text{EVENT}_t + \beta_4 \times \text{MCAP}_{i,t} + \beta_5 \times \text{INVERSE-PRICE}_{i,t} + \beta_6 \times \text{MARKET-VOL}_t + \beta_7 \times \text{ROLLOVER-DUMMY}_t + \epsilon_{i,t} \quad (1)$$

where $\text{MEASURE}_{i,t}$ is one of the OTR or market quality measures described in Section 4.1 for stock ‘i’ on day ‘t’. TREATED_i is a dummy variable which takes the value of one for a treated stock, zero otherwise. The estimated coefficient captures the pre-treatment mean differences in market quality variables across the two groups. EVENT_t is a time dummy which takes the value of one for the period post the fee imposition, and zero otherwise. 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.

³⁰We note that the average value of $|\text{VR-1}|$ 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 $|\text{VR-1}|$ 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.

Market variable	Treated SSF		Treated spot		Control spot	
	Mean	SD	Mean	SD	Mean	SD
Panel A: Event 1						
OTR	25.82	8.35	1.30	0.35	1.10	0.32
QSPREAD (%)	0.19	0.07	0.06	0.02	0.08	0.05
IC _{250k} (%)	0.20	0.07	0.16	0.05	0.24	0.13
IC _{500k} (%)	0.24	0.09	0.21	0.07	0.30	0.14
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

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 is measured as the realised volatility of intra-day returns on market index (MARKET-VOL_t). This captures 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 derivatives trading from October 2012.³¹ 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. In order 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.

³¹In 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 derivatives 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 $\times$ 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 (0.439)	0.046** (2.121)	2.564** (4.079)	1.604** (3.627)
Treated	24.736** (18.809)	0.274** (4.67)	60.914** (8.52)	0.908 (0.691)
Treated $\times$ Event	-4.211** (-3.81)	0.331** (5.481)	7.669 (0.654)	4.243 (1.454)
Market cap	-0.255 (-0.505)	0.047 (0.838)	0.512 (0.234)	0.599 (0.884)
Inverse Price	0.099 (1.52)	-0.022 ** (-4.416)	-0.19 (-1.855)	-0.106 ** (-3.241)
Market Vol	-0.021 (-0.911)	-0.003 ** (-2.458)	0.246 (1.889)	-0.022 (-1.803)
Rollover	5.695** (4.008)	0.012 (0.524)	0.685 (0.596)	0.65** (1.992)
Excluded			-3.579 (-0.239)	-6.167 (-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.

Table 5 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. 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 5 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 non-institutional-non-proprietary (NINP) traders. The dependent variable is the stock-day value-weighted average of the OTR across orders. ‘Treated $\times$ 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 (0.935)	0.121 (1.879)	0.081 (0.195)	0.036 (1.952)	0.05 (1.072)	0.045 (0.678)
Treated	17.784** (15.632)	4.116** (11.682)	42.979** (14.996)	0.2** (3.308)	0.026 (0.446)	0.283 (1.517)
Treated $\times$ Event	-4.605** (-4.936)	-0.723 (-1.837)	-3.092 (-1.184)	0.13** (3.657)	-0.051 (-0.986)	0.926** (4.78)
Market cap	-0.857 (-1.633)	-0.191 (-1.139)	0.013 (0.007)	-0.011 (-0.413)	-0.031 (-1.216)	0.301 (1.247)
Inverse Price	0.136 (1.922)	-0.003 (-0.158)	-0.015 (-0.096)	-0.012** (-3.332)	-0.008 (-1.958)	-0.061** (-4.376)
Market Vol	-0.025 (-1.163)	0.007 (0.855)	-0.015 (-0.293)	-0.003** (-3.641)	-0.001 (-0.445)	-0.009** (-2.744)
Rollover	3.997** (3.692)	0.591 (1.795)	13.311** (4.029)	0.013 (0.639)	0.007 (0.214)	0.006 (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

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 6. Not surprisingly, we find that there is a significant reduction in the OTR for those orders.

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

Table 6 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 $\times$ 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) ORDERS-BEYOND	Treated(Spot)-Control(Spot) ORDERS-BEYOND
Event	-1.545 (-1.023)	-2.153 (-1.419)
Treated	-4.272 (-1.134)	7.474** (2.218)
Treated $\times$ Event	-13.116** (-4.173)	-8.749** (-3.116)
Market Cap	-0.987 (-0.869)	-0.705 (-0.563)
Inverse Price	0.386** (4.287)	0.461** (4.141)
Market Vol	-0.004 (-0.046)	-0.169** (-3.776)
Rollover	1.174 (1.132)	2.07** (2.899)
Excluded	12.142** (2.544)	11.252** (2.935)
Adjusted R ²	0.18	0.22
# of obs	7485	9514

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.

5.2 Impact on liquidity

Tables 7 and 8 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 7). The estimates are negative and statistically significant for the transactions cost measures.

Table 7 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 $\times$ 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 (1.54)	-0.016** (-2.188)	-0.017 (-1.874)	0.025 (0.717)	0.038 (1.034)	0.042 (1.129)	0.035 (0.936)	-0.243 (-0.623)
Treated	0.125** (9.513)	-0.032 (-1.617)	-0.046** (-2.029)	1.884** (20.978)	1.668** (20.062)	1.649** (19.939)	1.64** (19.859)	-1.255 (-1.588)
Treated $\times$ Event	-0.058** (-6.888)	-0.03** (-2.599)	-0.046** (-3.408)	0.137** (2.739)	0.153** (2.778)	0.146** (2.683)	0.144** (2.687)	-1.167** (-2.136)
Market cap	-0.013 (-1.862)	-0.02 (-1.783)	-0.024 (-1.878)	0.046 (1.106)	0.058 (1.239)	0.054 (1.139)	0.048 (1.006)	-0.542 (-1.25)
Inverse Price	-0.001 (-0.744)	-0.001 (-1.178)	0.000 (-0.087)	0.025** (2.273)	0.031** (3.857)	0.029** (3.739)	0.027** (3.662)	-0.04 (-0.927)
Market Vol	0.002** (9.364)	0.004** (13.398)	0.005** (13.19)	-0.011** (-7.786)	-0.014** (-10.191)	-0.014** (-9.971)	-0.015** (-10.09)	0.162** (7.717)
Rollover	0.011** (2.195)	-0.003 (-0.557)	-0.008 (-1.023)	0.11** (5.413)	0.125** (4.891)	0.123** (4.508)	0.119** (4.181)	-0.184 (-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 (-1.368)	-0.018** (-2.523)	-0.02** (-2.194)	-0.003 (-0.098)	0.023 (0.619)	0.026 (0.702)	0.018 (0.471)	-0.347 (-0.888)
Treated	-0.016** (-2.558)	-0.074** (-4.155)	-0.08** (-3.896)	0.447** (5.2)	0.453** (5.46)	0.411** (4.897)	0.368** (4.33)	-2.303** (-3.224)
Treated $\times$ Event	0.002 (0.51)	0.007 (0.792)	0.005 (0.408)	0.202** (4.213)	0.193** (3.721)	0.201** (3.719)	0.217** (3.906)	0.326 (0.666)
Market cap	-0.003 (-0.752)	-0.019 (-1.898)	-0.024** (-2.084)	0.174** (2.263)	0.16** (2.114)	0.158** (2.05)	0.154 (1.952)	-0.505 (-1.311)
Inverse Price	0.000 (0.543)	0 (-0.22)	0.001 (0.738)	0.04** (5.311)	0.042** (7.217)	0.04** (7.263)	0.038** (7.313)	-0.029 (-0.789)
Market Vol	0.001** (9.544)	0.004** (12.869)	0.004** (13.006)	-0.014** (-10.408)	-0.015** (-10.127)	-0.016** (-9.768)	-0.016** (-9.892)	0.141** (7.296)
Rollover	-0.002 (-1.827)	-0.015** (-6.777)	-0.02** (-5.632)	0.1** (6.808)	0.102** (5.735)	0.1** (5.29)	0.095** (4.749)	-0.462 (-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

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).³²

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 7 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, our analysis of Event 2 finds little evidence that there was either a direct or indirect impact of the fee on market liquidity. This is consistent with our finding that the OTR fee did not have an impact on the aggregate OTR in Event 2. Panel A in Table 8 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. We conclude that there was a limited impact of the fee in Event 2 on market liquidity.

5.3 Impact on efficiency

Table 9 and 10 present the DiD estimations results on the impact of the fee of Event 1 and Event 2 on market efficiency measures. 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

³²A similar adverse impact of the French financial transaction tax was also found by Colliard and Hoffmann (2017).

Table 8 DiD estimates for the impact of the 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 $\times$ 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** (-2.073)	-0.029** (-3.879)	-0.034** (-3.605)	0.093 (1.875)	0.115** (2.06)	0.124** (2.229)	0.13** (2.414)	-0.916** (-2.511)
Treated	0.106** (8.238)	-0.039** (-2.26)	-0.047** (-2.052)	2.119** (16.757)	1.794** (13.982)	1.752** (13.551)	1.744** (13.558)	-1.79** (-2.662)
Treated $\times$ Event	-0.041** (-3.132)	-0.009 (-0.547)	-0.017 (-0.838)	0.088 (0.975)	0.127 (1.312)	0.113 (1.163)	0.091 (0.955)	0.052 (0.088)
Market cap	-0.009 (-1.927)	-0.023** (-4.209)	-0.024** (-3.51)	0.141** (3.417)	0.12** (2.149)	0.13** (2.21)	0.134** (2.244)	-0.728** (-3.403)
Inverse Price	0.002** (9.383)	0.002** (2.927)	0.004** (2.658)	0.027** (4.587)	0.024** (4.045)	0.022** (3.743)	0.02** (3.502)	0.07** (1.982)
Market Vol	0.001** (5.54)	0.001** (5.995)	0.001** (4.335)	-0.003** (-4.188)	-0.004** (-4.493)	-0.003** (-4.165)	-0.003** (-4.039)	0.033** (2.454)
Rollover	-0.003 (-1.538)	-0.005 (-1.087)	-0.014 (-1.519)	0.000 (-0.012)	-0.015 (-0.4)	-0.007 (-0.187)	-0.014 (-0.407)	-0.354 (-0.92)
Excluded	0.052** (2.832)	0.038 (1.72)	0.057** (1.983)	-0.25 (-1.661)	-0.315** (-1.993)	-0.307 (-1.93)	-0.266 (-1.726)	1.248 (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** (-2.358)	-0.026** (-3.421)	-0.03** (-3.159)	0.071 (1.42)	0.097 (1.74)	0.106 (1.909)	0.112** (2.094)	-0.925** (-2.528)
Treated	-0.003 (-0.615)	-0.018 (-1.024)	-0.001 (-0.022)	0.347** (3.05)	0.349** (2.837)	0.352** (2.799)	0.369** (2.908)	-0.669 (-0.979)
Treated $\times$ Event	-0.005 (-1.5)	-0.017 (-1.491)	-0.03** (-1.995)	0.205** (2.295)	0.185 (1.901)	0.193** (1.975)	0.195** (2.021)	-0.283 (-0.596)
Market cap	-0.003 (-1.864)	-0.027** (-4.748)	-0.032** (-4.237)	0.207** (3.005)	0.181** (2.293)	0.188** (2.319)	0.189** (2.284)	-0.823** (-4.048)
Inverse Price	0.002** (17.458)	0.002** (3.446)	0.004** (3.17)	0.031** (5.945)	0.027** (5.054)	0.025** (4.689)	0.023** (4.341)	0.088** (2.755)
Market Vol	0.001** (9.324)	0.002** (8.065)	0.002** (5.613)	-0.008** (-6.401)	-0.007** (-5.615)	-0.007** (-5.464)	-0.007** (-5.363)	0.031** (2.039)
Rollover	-0.001 (-1.698)	-0.004 (-1.326)	-0.007 (-1.325)	0.010 (0.525)	-0.019 (-0.786)	-0.012 (-0.511)	-0.014 (-0.626)	-0.436 (-1.927)
Excluded	0.010 (1.867)	0.056** (2.934)	0.069** (2.76)	-0.385** (-2.682)	-0.398** (-2.509)	-0.424** (-2.635)	-0.449** (-2.781)	1.754** (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

Table 9 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 (0.458)	-0.002 (-0.822)	-0.003 (-0.472)	0.005 (0.464)
Treated	5.708** (5.826)	-0.163** (-21.811)	-0.009 (-0.449)	-0.015 (-0.698)
Treated $\times$ Event	-3.507** (-5.826)	0.013** (2.391)	-0.048** (-4.067)	-0.066** (-4.354)
Market cap	-1.042 (-1.873)	0.006 (1.138)	-0.015 (-1.451)	-0.012 (-1.131)
Inverse Price	-0.031 (-0.678)	0.001 (0.891)	-0.003** (-2.767)	-0.003** (-2.959)
Market Vol	0.227** (12.728)	-0.001** (-6.866)	0.003** (8.711)	0.003** (8.219)
Rollover	0.041 (1.327)	-0.004 (-0.61)	0.02** (1.983)	0.018 (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 (-1.902)	0.001 (0.458)	-0.006 (-0.809)	0.002 (0.214)
Treated	-1.937** (-3.304)	0.002 (0.622)	-0.042** (-2.321)	-0.051** (-2.577)
Treated $\times$ Event	0.168 (0.574)	-0.002 (-0.512)	-0.007 (-0.739)	-0.011 (-0.823)
Market cap	-0.438 (-1.254)	0.005 (1.857)	-0.013 (-1.428)	-0.011 (-1.124)
Inverse Price -0.006	0.002** (-0.225)	-0.002** (8.448)	-0.003** (-2.664)	-0.003** (-3.513)
Market Vol	0.131** (14.986)	-0.001** (-7.004)	0.002** (8.293)	0.003** (8.055)
Rollover	-0.244** (-2.358)	0.005 (1.635)	-0.011** (-2.976)	-0.013** (-2.204)
Adjusted R ²	0.15	0.11	0.1	0.09
# of obs	6715	6715	6713	6689

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 would therefore reduce volatility and worsen efficiency, at least in the short term.

Interestingly, this decline is not visible for 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 Appendix). 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 9). 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 10). 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

While our results show that curbing excessive orders improved liquidity supply, it does not establish the channel through which these orders impacted the incentives of those who offer liquidity. We explore two specific channels, adverse selection and inventory management, as described in our hypothesis.

Brogaard *et al.* (2015) test the impact of these channels on liquidity suppliers following an optional colocation upgrade at NASDAQ OMX Stockholm. We follow the same approach to determine the impact of OTR fee on adverse selection and inventory management costs for liquidity suppliers. 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 the 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 inventory risk.

We use the DiD estimation described earlier using value-weighted stock-day averages across

Table 10 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 $\times$ 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	-0.534** (-2.52)	-0.001 (-0.382)	-0.025** (-3.126)	-0.029** (-2.337)
Treated	6.030** (6.195)	-0.127** (-17.487)	-0.022 (-1.317)	-0.025 (-1.186)
Treated $\times$ Event	-2.844** (-2.956)	0.011 (1.404)	-0.001 (-0.112)	-0.009 (-0.57)
Market cap	-0.719** (-2.09)	0.014** (3.347)	-0.008 (-1.441)	-0.005 (-0.7)
Inverse Price	0.137** (8.444)	0.002** (9.39)	0.001 (1.255)	0.001 (1.19)
Market Vol	0.042** (3.942)	0.000 (-0.152)	0.001** (3.49)	0.001** (2.062)
Rollover	-0.176 (-0.793)	-0.006 (-1.372)	0.008 (1.36)	-0.008 (-1.127)
Excluded	3.813** (2.885)	-0.01 (-0.95)	0.043** (2.449)	0.06** (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** (-2.547)	-0.002 (-0.466)	-0.024** (-2.937)	-0.026** (-2.151)
Treated	-0.820** (-2.133)	0.010 (1.854)	-0.02 (-1.271)	-0.012 (-0.582)
Treated $\times$ Event	-0.368 (-1.231)	0.011** (2.094)	-0.005 (-0.465)	-0.012 (-0.758)
Market cap	-0.364** (-2.26)	0.008** (3.763)	-0.006 (-1.311)	-0.004 (-0.719)
Inverse Price	0.143** (12.402)	0.002** (12.67)	0.001 (1.601)	0 (0.881)
Market Vol	0.053** (7.537)	0.000 (-0.992)	0.001** (5.677)	0.001** (2.918)
Rollover	-0.149 (-1.448)	-0.01** (-3.107)	0.002 (0.529)	-0.003 (-0.595)
Excluded	1.167** (2.485)	-0.024** (-2.98)	0.053** (3.395)	0.076** (3.335)
Adjusted R ²	0.58	0.2	0.09	0.03
# of obs	9515	9515	9512	9415

passive orders for these measures as our dependent variable for the two events separately. The estimations are done for the full sample (“All”) as well as for different trader categories. Table 11 provides the results of our estimations.

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

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 cost of inventory management, however, does not change much. This suggests that the improvement in liquidity came entirely from a reduction in adverse selection.

Our results indicate that the fee, though detrimental to faster liquidity suppliers, benefited the slower liquidity suppliers significantly enough to improve overall market liquidity. Our results are consistent with Shkilko and Sokolov (2020) who also use a natural experiment to show that adverse selection and trading costs decline when speed differentials across

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

liquidity suppliers are removed. An OTR fee has a similar effect in homogenising speed differentials between fast and slow liquidity suppliers. 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, suggesting lower adverse selection (see Table 12).

Our results contrast with those of Friederich and Payne (2015) and Malinova *et al.* (2018) who see a deterioration of market liquidity when OTR fee is applied on all orders. We believe that it could be due to a much smaller proportion of slower liquidity suppliers in the markets that they study.³³ The negative impact on faster liquidity suppliers must outweigh the benefit conferred by the fee on slower liquidity suppliers in their data.

This spillover benefit to slower liquidity suppliers vanishes when fast liquidity suppliers are not disadvantaged by the OTR fee, as in the case of Event 2. This result is consistent with Jorgensen *et al.* (2018) who also find that market liquidity does not change when OTR fee is introduced in Oslo Stock Exchange for orders other than market making orders. Our results highlight the importance of design (i.e., how the fee is implemented) for achieving the intended impact for interventions such as the OTR fee.

In our analysis of the effect of the OTR fee on market quality, we find that liquidity improved for both the SSF as well as for their underlying spot market. While our analysis reveals how the OTR fee changed the behaviour of the liquidity providers who face lower adverse selection costs, how the fee affects the motivations of traders in the control spot market is less obvious. There are barrier to establishing the channel for this transmission in the form of data limitations.

If orders and trades could be linked to unique identities, it would have been possible to trace how traders optimize across both markets after the fee. Jorgensen *et al.* (2018) use individual trader identities to determine whether traders modified their strategies to avoid paying the fee. They show that traders with high OTRs at the beginning of the month cut back on their order submission intensity later in the month to bring themselves under the threshold for the fee. In our case, aside of managing the OTR level within the month, high message-intensive traders could also move some of their orders to the spot market, or keep them within the 1% price threshold to claim exemption after Event 2. Similarly, Malinova *et al.* (2018) use trader-level data to compute intra-day returns for different trader types before and after the fee which would not be possible in an aggregated data like ours. Examining changes in returns will directly allow us to test whether message-intensive traders are able to preserve their profitability by modifying their strategies post the fee. Also, the lack of trader-level data prevents us from attributing the reduction in OTR and adverse selection for NINP category to the fund managers who use algorithmic trading.

³³HFTs accounted for more than three-fourths of all orders in their samples as opposed to around 20 percent around Event 1 in our analysis.

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 OTR 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 not penalise 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 consolidated and highly liquid, so that 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 which are 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 which have futures that are subject to a fee 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 excessive order placement and cancellations. 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 rate of order submissions 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.

Furthermore, we find that the excessive order activity 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. These results provide additional insights to understanding the mixed results recorded by earlier literature on the impact of such interventions.

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

References

- Aggarwal N, Thomas S (2014). “The causal impact of algorithmic trading on market quality.” *Working paper*, IGIDR WP 2014-023.
- Aggarwal N, Thomas S (2019). “When stock futures dominate price discovery.” *Journal of Futures Markets*, **39**(3), 263–278.
- Ait-Sahalia Y, Saglam M (2017). “High frequency market making: Implications for liquidity.” *Technical report*, Princeton University.
- Amihud Y (2002). “Illiquidity and stock returns: cross-section and time-series effects.” *Journal of Financial Markets*, **5**(1), 31 – 56.
- Anderson L, Andrews E, Devani B, Meuller M, Walton A (2021). “Speed segmentation on exchanges: Competition for slow flow.” *Journal of Financial Markets*. URL <https://doi.org/10.1016/j.finmar.2021.100632>.
- Angel JJ, Harris LE, Spatt CS (2011). “Equity trading in the 21st century.” *The Quarterly Journal of Finance*, **1**(1), 1–53.
- Baldauf M, Mollner J (2021). “Fast traders make a quick buck: The role of speed in liquidity provision.” *Journal of Financial Markets*. URL <https://doi.org/10.1016/j.finmar.2021.100621>.
- Baruch S, Glosten L (2013). “Fleeting Orders.” *Technical report*, Columbia Business School Research Paper.
- Benos E, Sagade S (2016). “Price discovery and the cross-section of high frequency trading.” *Journal of Financial Markets*. URL <https://dx.doi.org/10.1016/j.finmar.2016.03.004>.
- Biais B, Foucault T, Moinas S (2015). “Equilibrium fast trading.” *Journal of Financial Economics*, **116**(2), 292 – 313.
- Bloomfield R, O’Hara M, Saar G (2009). “How Noise Trading Affects Markets: An Experimental Analysis.” *Review of Financial Studies*, **22**(6), 2275–2302.
- Boehmer E, Fong K, Wu J (2018). “Algorithmic Trading and Market Quality: International Evidence.” *Working paper*. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2022034.
- Boehmer E, Fong K, Wu J (2020a). “Algorithmic Trading and Market Quality: International Evidence.” *Journal of Financial and Quantitative Analysis*.
- Boehmer E, Jones CM, Zhang X (2020b). “Potential pilot problems: Treatment spillovers in financial regulatory experiments.” *Journal of Financial Economics*, **135**(1), 68–87.

- Bohmer E, Shankar RL (2014). “Low latency trading and the comovements of order flow, prices and market conditions.” *Working paper*. URL <http://www1.nseindia.com/research/content/BS3.pdf>.
- Brogaard J, Hagstromer B, Norden L, Riordan R (2015). “Trading fast and slow: colocation and liquidity.” *Review of Financial Studies*, **28**(12), 3407–3443.
- Brogaard J, Hendershott T, Riordan R (2014). “High-frequency trading and price discovery.” *Review of Financial Studies*, **27**(8), 2267–2306.
- Brunnermeier M, Pedersen LH (2009). “Market liquidity and funding liquidity.” *Review of Financial Studies*, **22**(6), 2201–2238.
- Budish E, Cramton P, Shim J (2015). “The high-frequency trading arms race: Frequent batch auctions as a market design response.” *The Quarterly Journal of Economics*, **130**(4), 1547–1621.
- Capelle-Blancard G (2017). “Curbing the growth of stock trading? Order-to-trade ratios and financial transaction taxes.” *Journal of International Financial Markets, Institutions and Money*, **49**, 48 – 73.
- Carrion A (2013). “Very fast money: High-frequency trading on the NASDAQ.” *Journal of Financial Markets*, **16**(4), 680 – 711.
- Chaboud A, Chiquoine B, Hjalmarsson E, Vega C (2014). “Rise of the machines: Algorithmic trading in the foreign exchange market.” *The Journal of Finance*, **69**(5), 2045–2084.
- Chakrabarty B, Hendershott T, Nawn S, Pascual R (2019). “Order Exposure in High Frequency Markets.” *Working paper*. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3074049.
- Chakrabarty B, Tyurin K (2011). “Market Liquidity, Stock Characteristics and Order Cancellations: The Case of Fleeting Orders.” In GN Gregoriou, R Pascualau (eds.), “Financial Econometrics Modeling: Market Microstructure, Factor Models and Financial Risk Measures,” Palgrave Macmillan, London. URL https://doi.org/10.1057/9780230298101_2.
- Chen H, Foley S, Goldstein M, Ruf T (2017). “The Value of a Millisecond: Harnessing Information in Fast Fragmented Markets.” *Working paper*. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2860359.
- Colliard JE, Hoffmann P (2017). “Financial Transaction Taxes, Market Composition, and Liquidity.” *The Journal of Finance*, **72**(6), 2685–2716.
- Davies RJ, Kim SS (2009). “Using matched samples to test for differences in trade execution costs.” *Journal of Financial Markets*, **12**(2), 173 – 202.

- Fabozzi FJ, Focardi SM, Jonas C (2011). “High-frequency trading: Methodologies and market impact.” *Review of Futures Markets*, (9 Special issue), 7–38.
- Foucault T, Hombert J, Rosu I (2016a). “News trading and speed.” *The Journal of Finance*, **71**(1), 335–382.
- Foucault T, Kozhan R, Tham WW (2016b). “Toxic Arbitrage.” *The Review of Financial Studies*, **30**(4), 1053–1094.
- Foucault T, Moinas S (2018). “Is trading fast dangerous?” In W Mattli (ed.), “Global Algorithmic Capital Markets: High Frequency Trading, Dark Pools, and Regulatory Challenges,” pp. 9–27. Oxford University Press.
- Friederich S, Payne R (2015). “Order-to-trade ratios and market liquidity.” *Journal of Banking & Finance*, **50**, 214 – 223.
- Frino A, Mollica V, Webb R (2014). “The impact of co-location of securities exchanges and traders computer servers on market liquidity.” *Journal of Futures Markets*, **34**(1), 20–33.
- Hagstromer B, Norden L (2013). “The diversity of high-frequency traders.” *Journal of Financial Markets*, **16**(4), 741 – 770.
- Harris LE (2013). “What to do about high-frequency trading.” *Financial Analysts Journal*, **69**(2), 6–9.
- Harris LE, Panchapagesan V (2005). “The information content of the limit order book: Evidence from NYSE specialist trading decisions.” *Journal of Financial Markets*, **8**(1), 25 – 67.
- Hasbrouck J (2018). “High frequency quoting: Short-term volatility in bids and offers.” *Journal of Financial and Quantitative Analysis*, pp. 1–29. URL <https://doi.org/10.1017/S0022109017001053>.
- Hasbrouck J, Saar G (2013). “Low-latency trading.” *Journal of Financial Markets*, **16**(4), 646 – 679.
- Hendershott T, Jones CM, Menkveld AJ (2011). “Does algorithmic trading improve liquidity?” *The Journal of Finance*, **66**(1), 1–33.
- Hendershott T, Riordan R (2013). “Algorithmic trading and the market for liquidity.” *The Journal of Financial and Quantitative Analysis*, (4), 1001–1024.
- Hoffmann P (2014). “A dynamic limit order market with fast and slow traders.” *Journal of Financial Economics*, **113**(1), 156 – 169.
- Jarnecic E, Snape M (2014). “The provision of liquidity by high-frequency participants.” *Financial Review*, **49**(2), 371–394.

- Jorgensen K, Skjeltorp J, Arneodegaard B (2018). “Throttling hyperactive robots – Order-to-trade ratios at the Oslo Stock Exchange.” *Journal of Financial Markets*, **37**, 1–16.
- Jovanovic B, Menkveld AJ (2016). “Middlemen in Limit Order Markets.” *Technical report*, SSRN. URL <https://ssrn.com/abstract=1624329>, <http://dx.doi.org/10.2139/ssrn.1624329>.
- Kirilenko AA, Kyle AS, Samadi M, Tuzun T (2017). “The flash crash: The impact of high frequency trading on an electronic market.” *The Journal of Finance*, **72**(3), 967–998.
- Leone V, Kwabi F (2019). “High frequency trading, price discovery and market efficiency in the FTSE100.” *Economic Letters*, **181**, 174–177. URL <https://doi.org/10.1016/j.econlet.2019.05.022>.
- Lo AW, MacKinlay AC (1988). “Stock market prices do not follow random walks: evidence from a simple specification test.” *Review of Financial Studies*, **1**(1), 41–66.
- Malinova K, Park A, Riordan R (2018). “Do retail traders suffer from high frequency traders?” *Working paper*. URL http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2183806.
- Menkveld AJ (2013). “High frequency trading and the new market makers.” *Journal of Financial Markets*, **16**(4), 712 – 740.
- Nawn S, Banerjee A (2018). “Do Proprietary Algorithmic Traders Withdraw Liquidity during Market Stress?” *Financial Management*, **48**(2), 641–676.
- Nawn S, Banerjee A (2019). “Do the limit orders of proprietary and agency algorithmic traders discover or obscure security prices?” *Journal of Empirical Finance*, **53**, 109–125.
- NSE (2009). “Levy of charges to deter system abuse in the F&O Segment.” *NSE Circular No: NSE/F&O/13029*. URL <https://www1.nseindia.com/content/circulars/faac13029.pdf>.
- NSE (2010). “Rationalisation of system abuse charges in the F&O Segment.” *NSE*. URL <https://www1.nseindia.com/content/circulars/faac14928.pdf>.
- NSE (2012). “Levy of charges for High Order to Trade Ratio.” *NSE*. URL <https://www1.nseindia.com/content/circulars/FA21156.pdf>.
- Pereira JP, Zhang HH (2010). “Stock returns and the volatility of liquidity.” *Journal of Financial and Quantitative Analysis*, **45**(4), 1077–1100.
- SEBI (2012a). “Broad guidelines on algorithmic trading.” *SEBI CIR/MRD/DP/09/2012*. URL https://www.sebi.gov.in/cms/sebi_data/attachdocs/1333109064175.pdf.

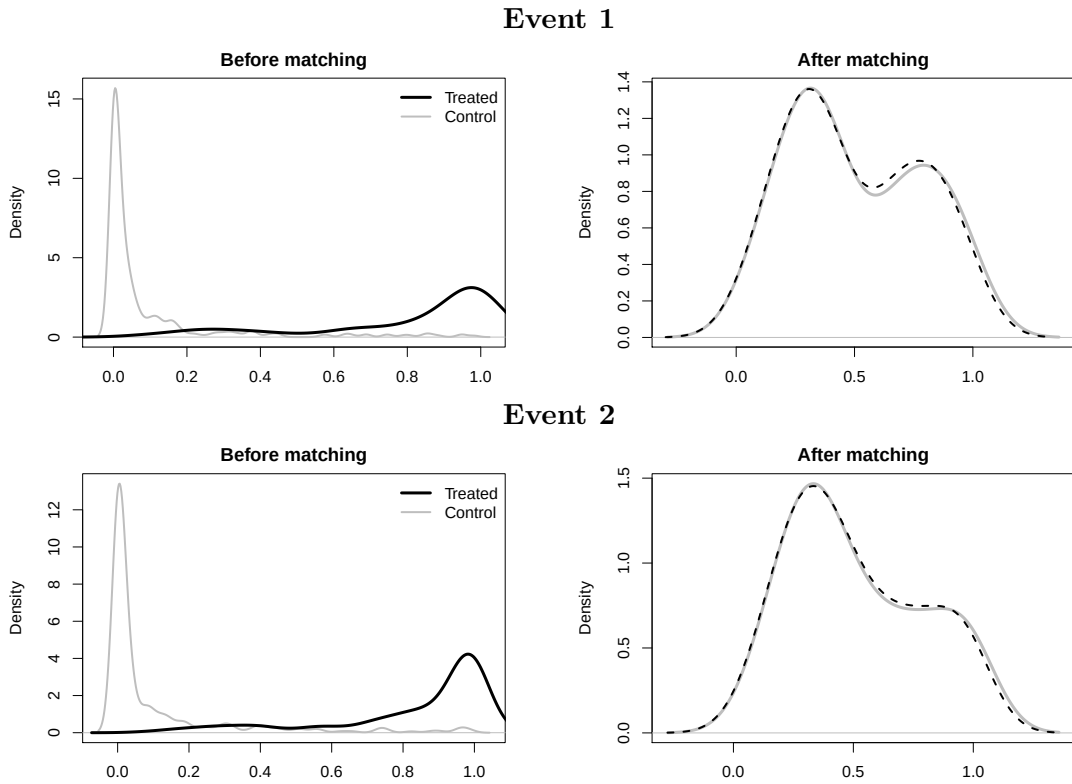
- SEBI (2012b). “Revision of Eligibility Criteria for Stocks in Derivatives Segment.” *SEBI*. URL https://www.sebi.gov.in/legal/circulars/jul-2012/revision-of-eligibility-criteria-for-stocks-in-derivatives-segment_23131.html.
- SEBI (2013). “Broad guidelines on algorithmic trading.” *SEBI CIR/MRD/DP/16/2013*. URL https://www.sebi.gov.in/sebi_data/attachdocs/1369137134098.pdf.
- Shkilko A, Sokolov K (2020). “Every cloud has a silver lining: Fast trading, microwave connectivity and trading costs.” *Journal of Finance*, **LXXV**(6). URL <https://doi.org/10.1111/jofi.12969>.
- Tobin J (1978). “A Proposal for International Monetary Reform.” *Eastern Economic Journal*, **4**, 153–159.
- Umlauf SR (1993). “Transaction taxes and the behaviour of the Swedish stock market.” *Journal of Financial Economics*, **33**(2), 227–240.

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 t	KS	μ_{tr}	μ_{cr}	p-value t	KS
<i>Panel A: Event 1</i>								
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
<i>Panel B: Event 2</i>								
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.

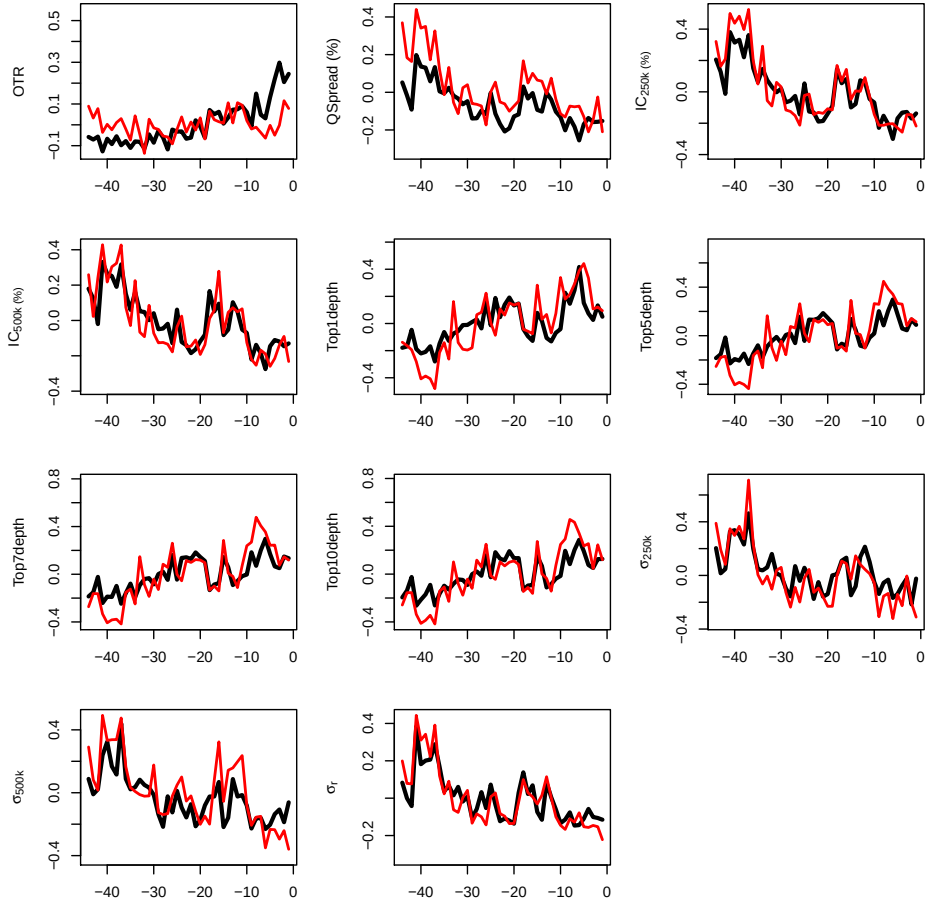
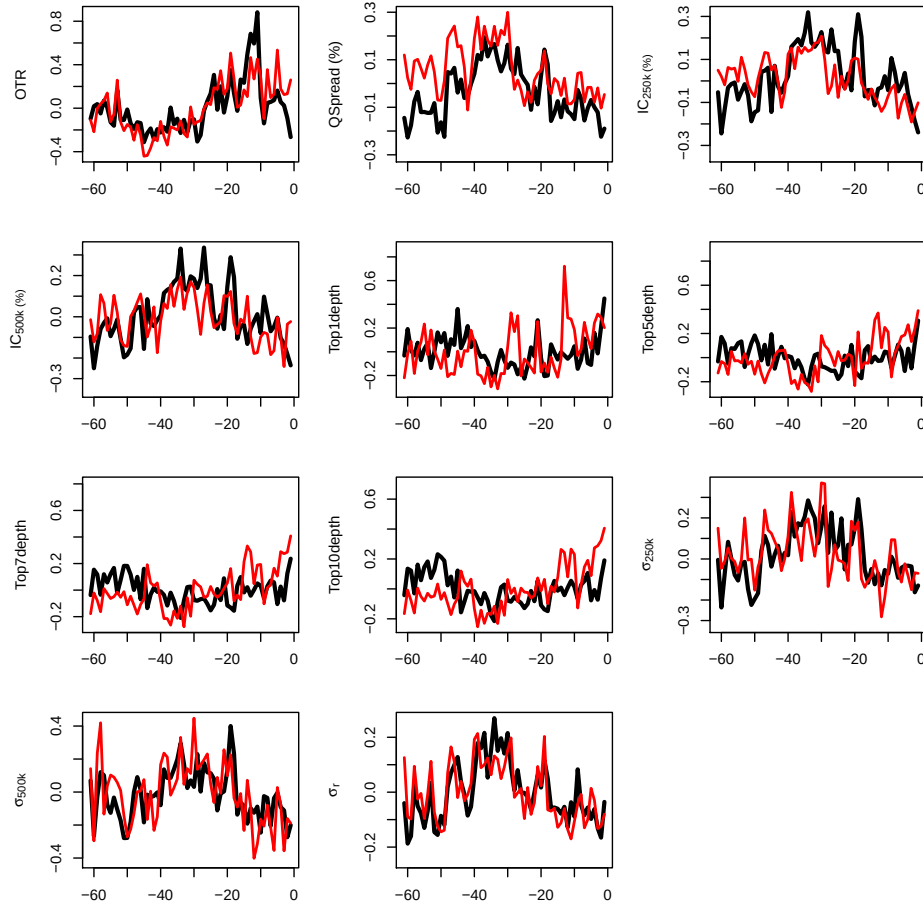


Figure B.2 Pre-treatment outcome variables for matched treated and control stocks on the spot market around Event 2

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