When do regulatory hurdles work?

Nidhi Aggarwal* Venkatesh Panchapagesan† Susan Thomas‡

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Abstract

The paper analyses two instances when an orders-to-trades ratio fee was used as a hurdle to algorithmic trading in the Indian equity market. In the first instance, the fee was charged by the exchange to manage the increased load on limited exchange bandwidth, while in the second, the fee was used by the regulator to address public policy concerns. We use a difference-in-difference estimation strategy to identify the causal impact of the fee in both instances, on market quality. We find that the orders-to-trades ratio reduced, on average, after the first fee was imposed. Liquidity improved and liquidity risk decreased. But there was little or no change in the orders-to-trades ratio or market quality in response to the second fee. We conclude that interventions with a clearly defined objective to solve a market failure are more likely to realise desired outcomes.

*Nidhi Aggarwal is with the Indian Institute of Management, Udaipur. Email address: `nidhi5.2003@gmail.com`

†Venkatesh Panchapagesan is at the Indian Institute of Management, Bangalore. Email address: `venky@iimb.ac.in`

‡Susan Thomas is with the IGIDR, Bombay. Email: `susant@igidr.ac.in` This is the second draft of the paper which has a different sample and a new methodology that is more robust to endogeneity issues compared to the first draft. We thank the discussants at the 5^{th} Emerging Markets Finance conference for comments on the first draft, at the Field workshop on financial securities markets, October 2017, at the International Conference on Market Design and Regulation in the Presence of High-Frequency Trading organised by Global Research Unit at Department of Economics and Finance, City University of Hong Kong and Center for Analytical Finance, University of California Santa Cruz, December 2017, and at the 11th Financial Risks International Forum, organised by Institut Louis Bachelierfor, March 2018, for comments and suggestions on this draft. The findings and opinions presented in this paper are those of the authors and not of their employers. All errors remain our own.

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1 Introduction

High trading activity in financial markets has often attracted apprehension from policy makers. This has been particularly true after the global credit crisis of 2008, and with the growing dominance of high-frequency trading. Such fears, which are driven by public policy concerns, persist despite evidence that the high levels of trading activity give rise to better market liquidity, and often lead to policy interventions to curb algorithmic trading activity. Some of these interventions are in the form of slowing down the algorithmic trading and others in the form of charges on trading. Transactions taxes is an example of the latter and introducing delays in orders before being modified is an example of the former. These interventions often documented as leading to adverse outcomes for the market. For example, when the Norwegian countries imposed a transactions tax on equity trading in the 1980's, local trading activity and price discovery migrated to competing financial markets in the Euro-zone. Nevertheless, the concerns continue to persist. Policy makers continue to focus on designing interventions hurdles to algorithmic and high frequency trading.

This paper exploits an opportunity to study the impact of one such policy intervention, which is in the form of a fee on high levels of transactions. One example is the *orders-to-trades fee*, or the OTR fee. This fee is charged based on whether the orders to trades ratio in the market is higher than a selected policy threshold. Over the previous decade, several exchanges have experimented with the use of an OTR fee to control high frequency trading starting with the Chicago Mercantile Exchange which implemented a fee in 2005. Recent literature documents the impact of these fees at exchanges in Canada, Italy and Norway (Friederich and Payne, 2015; Jorgensen *et al.*, 2017; Capelle-Blancard, 2017). In most of these, the intervention appears to have an uncertain effect on the dominance of high frequency trading and a negative effect or no effect on market quality. The impact varies across different markets but in all cases, the cost of the intervention (in the form of implementation by the exchanges, the traders and the actual penalties that are incurred) appear to be higher than any benefits.

The Indian equity derivatives markets presents a new perspective within which to understand the effect of a fee on high frequency trading. The Indian equity market has been ranked as one of the top exchange in the world by number of transactions on single stock derivatives.Algorithmic trading was permitted in 2008. After exchanges started co-location services at the start of 2010, that the fraction of trades in the market that could be attributed to algorithmic trading went from an average of 10 percent to 60 percent by 2015.

Since 2008, the OTR fee was used multiple times. The first implementation of this fee was by an exchange. The exchange used the OTR fee, between 2009 and 2010, to better manage sparse bandwidth. In 2012 and then in 2013, the securities market regulator used the OTR fee to address public policy concerns about algorithmic trading. In all these cases, the fee was used to reduce the amount of algorithmic trading in the market. The analysis in the paper attempts to identify how effective the fee was in achieving the desired objective, as well as to assess the causal impact of the fee on market quality.

The identification strategy is based on the observation that the OTR fee is applied to the equity derivatives markets, but no fee was imposed on the underlying spot markets. This suggests that the underlying securities can be used to identify a control using which to measure the causal impact of the fee on the derivatives. In the paper, we use single stock futures as the treated set (on which the OTR fee is applicable). We create two sets of controls from the spot market: one control set are underlying stocks on which there are traded single stock futures, and another control are stocks which do not have futures trading on them.

Stocks with futures present the natural control where the futures are the treated set in a difference-in-difference regression. But there is likely to be an endogeneity bias in these regressions. Single stock futures and the underlying spot present a trade-off between the benefits of leverage and liquidity when taking an exposure on the same security (Brunnermeier and Pedersen, 2009; Aggarwal and Thomas, 2011). An increase in the transaction in stock futures (such as the OTR fee) is likely to cause a shift of capital to the underlying spot market. Thus, an OTR fee can have an indirect effect on the underlying spot.

Therefore, the second control is set up in order to tackle this endogeneity bias, where stocks with futures become the treated set and matched stocks without futures is the control. If the fee has a causal impact on the single stock futures relative to the underlying spot, then the OTR fee is also likely to have an impact on the relative behaviour of the stocks with futures relative to a matched stock without futures.

We use both treated-control sets in difference-in-difference estimations to infer the impact of the OTR fee. The dependent variables in these estimations include the OTR level, market liquidity measured by the estimated impact cost of transactions for two different sizes, and market efficiency measured by the variance ratio of returns and the volatility of the impact cost.

In this paper, we study two instances when the OTR fee was implemented: the first instance when the exchange imposed the fee in 2009, and the first instance when the securities markets regulator imposed the fee in 2012.

We find that, after the first fee in 2009, the average OTR level in the single stock futures *reduced* relative to the OTR in the underlying spot, while OTR of the underlying spot *increased* relative to matched control stocks. This implies that the fee caused the OTR to drop.

In contrast, we do not find a clear causal impact for when the fee was implemented in 2013. After this implementation of the fee, there appears to be an *increase* in the OTR level of the single stock futures relative to their underlying as control, and *decrease* in the OTR level of the underlying relative to the stocks without futures as the control. This is counter to the regulatory objective to reduce the OTR in the market.

When we analyse the impact of the fee on market quality, market liquidity of the treated securities *improved* after the fee was imposed in 2009. The spread and impact cost *decreasd*, as did the volatility of liquidity. The results suggest that when the OTR fee was applied to manage the use of limited exchange bandwidth, it improved market quality. This is different from the literature on the impact of the OTR fee which has only reported a negative or no impact of the fee on market liquidity.

In comparison, there was little or no change caused by the fee that was imposed in 2013. The only significant evidence is that volatility of liquidity appears to have *increased* after the fee, particularly for orders which have prices away from the bid-ask price.

We conclude from these results that the 2009 fee was effective while the 2013 fee had ambiguous results. The 2009 fee was effective in reducing the dominance of algorithmic trading (lower OTR) while improving market quality (lower transactions costs, lower volatility of transaction costs). In comparison, the 2013 fee was ineffective in having any clear impact on the dominance of algorithmic trading, even though there was little impact on the market quality (higher volatility of transaction costs at larger trade sizes). In the cost-benefit analysis of the impact of the OTR fee as a regulatory intervention on algorithmic trading, we find that the fee appears to deliver visible, positive outcomes in only the 2009 implementation.

We hypothesise that the difference in the effectiveness of these two implementations is driven by the clarity of the stated objectives for the interventions.

The 2009 fee had a stated objective to use the fee to manage exchange access bandwidth. This led to a well-designed fee with a specific target, and the target was achieved. While the fee of 2013 had a public policy motivation which is less likely to lead to a well specified design of the fee. The results of the paper support the position that clearer regulatory objectives are likely to achieve the desired regulatory outcome. A similar inference is drawn by Jorgensen *et al.* (2017) who suggest a link between the design of the intervention and success in achieving a desirable regulatory outcome.

The paper is organised as follows: Section 2 presents the context of how high frequency trading has attracted regulatory interventions despite mounting evidence that market liquidity improves with increased levels of high frequency trading. Section 3 discusses existing research on applications of the OTR fee as a regulatory intervention to manage the effects of high frequency trading, and specifically instances when it has been used in the Indian equity markets and the research questions we ask in the paper. Section 4 describes the data and the methodology we use to measure the impact of the OTR fee. Section 5 describe the results of the analysis, and Section 6 concludes with what we learn and some suggestions on future research in this area.

2 High frequency trading and regulatory interventions

Algorithmic trading (AT) and high frequency trading (HFT) has been the dominant method of trading in exchange platforms for a while now. These forms of trading give traders one more mechanism to manage adverse selection risk of posting limit orders on the exchange platform, which provides the market with free trading options (Harris and Panchapagesan, 2005). These options can be valuable to others, but the submitting trader suffers a cost when the market moves away from these orders and they are picked off by other opportunistic traders. Traditionally, limit order traders have used a variety of strategies including hiding their true order size and pricing away from the market to protect these option values, especially when they are not able to monitor the markets closely. In recent times, growth in technology and the resultant reduction in latency has allowed these traders to protect their orders by modifying and canceling them easily in light of new information using AT. Without the adverse selection risk, these limit order traders are likely to compete more on price as well as on size. This is likely to have a positive effect on the

The increased use of technology in these forms of trading have had the added benefit of a greater degree of transparency about order flow and trades, which has offered advantages to both the traders as well as academics researching the behaviour of these markets. The resultant research has accumulated evidence that the dominance of algorithmic trading (AT) has improved market quality, on average.

The literature presents evidence about the impact of both AT and HFT as being mostly positive. For example, Hasbrouck and Saar (2013) study the effect of low latency AT over two distinct periods at the NASDAQ and find that higher levels of low latency activity correlates with better market quality. Hendershott *et al.* (2011) find that the NYSE auto quoting facility that was introduced in 2003 reduced effective spreads for all stocks and particularly for large cap stocks. Much of the work has been done for the US financial system (Angel *et al.*, 2011; Robert *et al.*, 2012; Avramovic, 2012; Easley *et al.*, 2012; Cumming *et al.*, 2012; Weisberger and Rosa, 2013; Bollen and Whaley, 2014) which are fragmented across a wide number of trading platforms and where aggregated information about algorithmic trading is difficult to obtain.

Increasingly, there is research on non-U.S. exchanges, where the extent of fragmentation is lower and data offers a higher level of transparency about whether the orders are algorithmic or not. For example, both the Deutsche Borse in Germany and the National Stock Exchange in India publish orders and trades data that are explicitly tagged as AT. Hendershott and Riordan (2009) study the data of the Deutsche Borse Xetra platform and find that AT contributes to discovery of prices and does not contribute to excess volatility. Others find trading latency is lower, liquidity is higher and adverse selection is lower once the trading system at the Deutsche Borse were upgraded (Hendershott and Moulton, 2011; Hendershott and Riordan, 2013). Aggarwal and Thomas (2014) carry out a difference-in-difference analysis on small and medium stocks at the National Stock Exchange of India that have a higher fraction of AT compared to control stocks, and find that stocks with higher AT intensity have higher liquidity, lower intra-day volatility of liquidity, lower volatility, and a lower likelihood of flash crashes compared to similar stocks with a lower fraction of AT.

Despite the growing evidence about the benefits of AT, there has also grown substantial discomfort and regulatory concerns about the effects of AT and HFT. Inevitably, there have been episodes of poorly constructed algorithms and ill-tested systems have brought exchange trading to a halt in the middle of a trading day, signs of market participants adjusting to electronic systems with algorithmic trading. There are episodes where there have been temporary extreme price movements and others with market closure during trading hours at exchanges. Some of the better known examples include the 6^{th} May 2010 'Flash Crash' in the U.S. markets, the crash at Tokyo Stock Exchange triggered by excessive trading of *Livedoor* stock (Brook, 2005), or the crash at the National Stock Exchange of India Ltd., (NSE) because of a fat-finger trade in the Nifty index futures (Aggarwal, 2017).

Thus, even though research indicates that HFTs are not the cause of such crashes (Kirilenko *et al.*, 2014), public opinion remains in favour of regulatory interventions to discourage HFT. And while exchanges and securities firms continuously invest in capacity to handle the new pressures on their systems because they benefit from the higher turnover that HFT brings, they also face the cost of technical errors and market closures when their trading systems get overloaded by HFT messaging traffic.

This persistent, ubiquitous discomfort lead to *public policy concerns* about HFT, which lead to regulators and exchanges to propose interventions which act as disincentives to HF traders for the potential negative externalities that they can impose on markets. For example, one proposal is a minimum resting time for orders before any action can be taken on them. Harris (2013) proposes that the exchange introduces a random delay between order arrival and order processing by the exchange of between 0 and 10 milliseconds. This introduces uncertainty in the latency of order placement and is likely to prevent a monopoly outcome among trading firms that chase cutting edge hardware systems in order to reach lowest latency. Another set of proposals is to explicitly tax HFT for canceling orders within a short period such as the orders-to-trade ratio fee, or an OTR fee. This is a charge or fee for order placement and trade execution strategies that generate a high orders to trade ratio. The Chicago Mercantile Exchange put in place an OTR fee in April 2005, which was charged if the OTR exceeded a threshold of 25 : 1.

2.1 Motivation for a fee on high orders-to-trade ratios (OTR)

As with any additional cost imposed in a market, the OTR fee is likely to have a negative effect on liquidity. As a consequence, this is likely to have a negative effect on price efficiency. However, since these interventions are driven by public policy concerns, they are designed to improve long-term investor confidence by reducing the chances of HFT being the source of an unexpected trading closure on exchanges, like the Flash Crash of 2010. If the intervention is effective, it will raise investor confidence which, in turn, should lead to greater trading compared to if these interventions were not implemented.

However, much of the empirical literature on the impact of the OTR fee suggest that it is more likely that the costs outweigh benefits. For example, Friederich and Payne (2015) and Capelle-Blancard (2017) find that a OTR fee imposed by the Italian Stock Exchange led to decreased trading activity in the aggregate. Jorgensen *et al.* (2017) tested the effects of an OTR fee in the Oslo Stock Exchange and found that traders responded in such a way to work around the fee. They report that the fee does not cause any adverse changes to average market liquidity.

In this paper, we have a unique opportunity to observe two events when an fee on OTR was imposed in the Indian equity derivatives markets. In the first event, the fee was imposed by the exchange to better manage HFT messaging pressure on their trading systems. The second instance of the fee was imposed by the regulator as a response to more broad public policy pressure. In both cases, the structure of the intervention was applied on the same market, the equity derivatives markets. But in each case, there were differences in the details of how the fee was imposed, and for whom it was relevant. In this paper, we set up an event study to capture the change caused by the fee. Further, we attempt to identify a control group of securities that traded in the market during the same time periods as when the fees were imposed. These are used to set up a difference-in-difference regression to identify causal effects. This allows us to evaluate the effect of the same regulatory instrument under two different objectives.

We describe the setting of the research design and the details of the research methodology in the following sections.

3 OTR fee regimes in the Indian equity markets

The markets that are used in the study are the equity spot and derivatives markets at the National Stock Exchange of India (NSE). The NSE is one of two equity stock exchanges in India,[1] with a market share of 75% on equity spot market, and about 98% on equity derivatives market (SEBI, 2013). The

[1]The other stock exchange is the Bombay Stock Exchange, BSE.

market micro-structure is described briefly as follows: Trading takes places from 9am to 3:30 pm through an anonymous continuous electronic limit order book mechanism, where orders are matched on a price time priority.[2] More than 1400 securities are listed at the equity platform of NSE, out of which 146 securities are traded on the derivatives platform. The selection of securities on the derivatives platform is based on the free float market capitalisation, average traded value and the price impact of an order on the stock. The securities markets is regulated by the Securities and Exchanges Board of India (SEBI). The regulatory context is such that the micro-structure for all the exchanges have to be permitted by the regulator who tends to be prescriptive in setting rules and regulations. As a consequence, the exchanges have the same trading times, follow the same parameters in introducing products on the exchange, as well as in how trading, clearing and settlement is implemented.

In keeping with the role of the regulator in deciding the market micro-structure, algorithmic trading was permitted by SEBI in equities in April 2008. Although exchange members started implementing algorithmic trading systems, it was only after the exchanges implemented *co-location*, that the intensity of algorithmic trading increased significantly as a percentage of the total trading.[3]

Since then, there have been multiple instances when a fee has been charged on the orders to trades ratio. The NSE put a fee on high OTR in equity derivatives in 2009 in order to reduce the load on exchange infrastructure. The exchange detected that there was a very high rate of Immediate and Cancel (IOC) orders that were used by traders to execute arbitrage strategies on derivative markets. A large proportion of these orders remained unexecuted but added significant load on the bandwidth.

In imposing a fee on orders-to-trades that were higher than a given threshold value, the exchange acted as a self-regulatory organisation that was seeking to ensure good market quality to stakeholders with an interest in the equity markets. The circular issued by the exchange states the objectives of the fee as:

> "Of late, it is observed that the Order to Trade ratio in the F&O segment has been increasing significantly. Based on the analy-

[2] The opening price is determined through a pre-open call auction mechanism conducted between 9am to 9:15am.

[3] Aggarwal and Thomas (2014) shows how AT intensity started from around 20 percent of the market in 2010 to 55-60 percent by 2013, with some stocks having a AT intensity of 70 percent.

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

The fee that was put in place at this time was applicable on equity derivatives. It was not applicable on trading activity in the equity spot markets. It was implemented uniformly across all market participants and all order types, without any exceptions. The exchange subsequently removed the fee in July 2010.

After this, there was no fee in equity market trading activity, until 2012, when the securities markets regulator, SEBI, issued a circular to market participants that a fee was to be imposed on high OTR. Like the exchange intervention, this was done without a prior public consultative process. However, unlike the exchange intervention, the objectives for which the fee is imposed was not to manage a specified or tangible problem but rather one of a general, public policy concern. SEBI (2012) says:

> "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 disincentive was a fee on OTR that was put in place in July 2012. When SEBI implemented the fee, it was levied in lieu of the *increased* usage of algorithms for trading by market participants. The fee was applicable *only* on algorithmic orders, along with several exceptions. For instance, all order entries that were placed, or modifications of orders with prices within one percent of the last traded price, were exempt from the fee. Orders from trading members who were designated as market makers were exempt from the fee.[4] The stated explanation for the exemptions was that the regulator

[4] In India, designated market makers are only for the illiquid indices. The stocks covered in this study did not have any designated market maker under the *Liquidity Enhancement*

wanted to minimise any adverse impact of the fee on the available liquidity at the best bid and ask prices in the limit order book. There was a further modification of fees in May 2013, when SEBI directed exchanges to double the magnitude of the fee SEBI (2013).[5]

Table 1 Details of the OTR fee implementations

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

In each regime, the fee was implemented *only* on equity derivatives. The details of the implementation of the OTR fee in the two regimes are summarised in Table 1. Further, we present the events when the OTR fee was imposed in the Indian equity markets in Figure 1. For a frame of reference, we impose these events on the graph showing the rise of algorithmic trading at the exchange in single stock futures. The solid horizontal line represents

Scheme (LES) under which exchanges were permitted to pay trading members a fee for maintaining two-way bids on select derivative contracts.

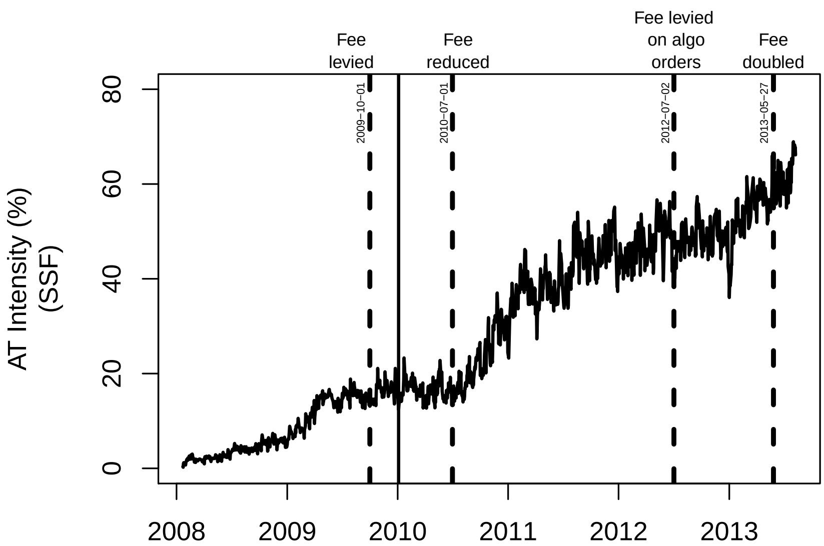
[5]The SEBI circular in 2013 is more specific about the nature of the disincentive compared to the circular in 2012. The 2013 circular states:

> "4. As directed vide circular dated March 30, 2012 stock exchanges have implemented a framework of economic disincentives for high daily order-to-trade ratio of orders placed from trading algorithms by prescribing penalties in form of 'charges to be levied per algo orders' at various levels of daily order-to- trade ratio. The penalty rates specified by the stock exchanges have been reviewed and in order to provide sufficient deterrence, stock exchanges are directed to double the existing rates of 'charges to be levied per algo orders' specified in their circulars / notices.
>
> 5. In order to discourage repetitive instances of high daily order-to-trade ratio, stock exchanges shall impose an additional penalty in form of suspension of proprietary trading right of the stock broker / trading member for the first trading hour on the next trading day in case a stock broker / trading member is penalized for maintaining high daily order-to-trade ratio, provided penalty was imposed on the stock broker / trading member on more than ten occasions in the previous thirty trading days.
>
> 6. The circular shall be applicable with effect from May 27, 2013."

the date on which the exchange put in place co-location services in January 2010. In the graph, the dashed horizontal lines mark the various dates of an OTR-based fee based interventions on equity derivatives. The first line is when the exchange first imposed the OTR fee. The second dashed line was when the exchange removed the fee. The third line was the instance when SEBI brought back the fee, but imposed it with restrictions, and the last line was when SEBI raised the fee imposed. The percentage of algorithmic trading was relatively low at around 20 percent when the exchange imposed the fee in late 2009 compared to the later period when SEBI imposed the fee, when the percentage attributed to algorithmic trading was significantly higher at around 60 percent for the overall market.

Figure 1 AT intensity in single stock futures at the National Stock Exchange

The graph shows the AT intensity on the single stock futures (SSF) market at NSE between 2009 and 2013.
AT intensity is measured as a fraction of the total traded value of AT trades in a day vis-a-vis the total traded value on that day. The vertical line in boldface indicates the date on which co-location was introduced by the exchange.
The first two dotted line indicate dates of the fee intervention by the exchange, and the last two dotted lines indicate the dates of the fee intervention by the regulator.



Algorithmic trading was thus a relatively new form of trading in 2009 when the exchange imposed the fee as a mechanism to manage limited bandwidth available for market access.

In this paper, we focus on the first event when the OTR fee was imposed by NSE in 2009 (NSE, 2009), and the second event when the OTR fee was mandated by SEBI in 2012 (SEBI, 2012; NSE, 2012). For these periods, we choose to ask the following questions:

Q1: Does the OTR fee have the intended impact of reducing the average level of the OTR?

Q2: What were the consequence of the fee on market liquidity?

Q3: What were the consequence in the fee on market efficiency?

We choose these two events because the design variations across these two events can be useful to identify what makes such a fee effective. For example, while the 2009 fee was imposed on *all* orders, the 2012 fee was only on algorithmic orders that were placed *outside* of the best bid and offer prices on the screen. A fee can be expected to increase the average cost of trading, and to reduce the average OTR in the market. Thus, the fee that was imposed in the 2009 period may be expected to have the effect of *reducing* the overall market-wide OTR. In turn, this is likely to lead to more adverse market qualities of efficiency and liquidity. However, if it is effective in managing bandwidth problems for various market participants, the fee may lead to improvements in market efficiency as well as market liquidity on average.

On the other hand, if the fee was imposed differentially for different participants or for orders in different parts of the limit order book, it would affect trading behaviour in different ways. This makes it difficult to predict how the average OTR was affected in the case when the OTR fee was re-introduced in 2012, or how it affected market efficiency and liquidity.

In our analysis, we attempt to answer questions about how the market responded to the imposition of an OTR fee. As part of the analysis, we attempt to identify the causal impact of the fee by comparing estimated changes in the market where the fee was imposed (equity derivatives) to a market with the same securities without leverage and there was no fee imposed (equity spot). In the following sections, we describe the data set and the research methodology used to answer the above questions related to the impact of the OTR fee.

4 Data and research methodology

The research methodology includes a description of the data used, the measures of OTR and market quality, and a description of the matching procedure and the regression specification to carry out the difference-in-difference estimation.

4.1 The data-set

We have access to a proprietary tick-level data-set of all orders and trades in the equity and equity derivatives segment of NSE. In addition to details about the type of order, the data provides the following details as categorical variables: a) trader type category (whether institutional, proprietary or neither of the two), b) if the order/trade was by an AT or non AT, (c) the type of order event (whether it was an order entry, modification or cancellation). This data is used to create the various measures of OTR, market liquidity and market efficiency around the time of introduction of the OTR fee.

Since there are two events, we use the data to calculate the OTR and market quality measures around these two events. For each event, our analysis examines the behaviour of the market for a three month window before the fee was imposed, and three months after. Thus, the data for the analysis includes the OTR as well as the eight market quality measures, in periods before and after the event, as follows:

For **Event 1** (Fee imposed by NSE on October 1, 2009)

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

For **Event 2** (Fee imposed by SEBI on July 2, 2012)

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

4.2 OTR measures

We compute the OTR for a stock in two different ways, at an order level and at the aggregate level.

For each unique order, the OTR is calculated as:

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

where the order events include entry, modifications and cancellations. In any given period, there many be several orders but no trades. We add 1 to the denominator of the ratio to make the ratio meaningful. The OTR is computed for each order on a stock in a day, which is then used to compute a value-weighted OTR average. We call this the VWTD OTR.

For the OTR at an aggregate level, we take the ratio of total number of messages for each stock for each day received by the exchange to total number of trades. The number of messages includes order entry, modification and cancellation. We call this the OTR NAIVE.

4.3 Market quality measures

The features of a market that signify quality is typically the liquidity and the price efficiency of the market. The greater the liquidity, the greater the market quality. Similarly, for a market with greater price efficiency. There are standard measures of both liquidity and efficiency used in the literature, and we use a subset of each for the analysis in this paper.

Liquidity measures We measure liquidity in two ways: as market transactions costs and as available depth.

Market transactions cost measures are *quoted spread* and *impact cost*. Quoted spread (or QSPREAD) captures the cost for a small order by examining the percentage difference between the ask and bid prices. Impact cost (or IMPACT COST) measures the instantaneous cost for a given order size.

For the analysis, we measure the impact cost at two order sizes: Rs 25,000 (approximately USD 380) and Rs. 250,000 (USD 3800). Although these transaction sizes are small by global standards, we use these because Rs.25,000 is the size of an average trade in the equity spot market, and Rs.250,000 is the lot size in the derivatives market.[6]

We also calculate the Amihud illiquidity measure (ILLIQ) (Amihud, 2002) as a measure that is widely used in the literature.

[6]Since the writing of this paper, the lot size in the derivatives markets have been increased to Rs.500,000 or approximately USD 7800.

Since the data allows us access to the full limit order book, we can measure the available depth in the market at any given point in time. This is used to calculate the following two *depth* measures: (1) the rupee value of orders that are available at the best prices in the limit order book (or TOP1DEPTH) and (2) the rupee value of orders that is available across the best five prices (or TOP5DEPTH).

The above six measures are computed for each stock at a second, and the median value is reported as the depth measure for the day. The exception to this is the ILLIQ measure, which is calculated directly as a daily value for each stock.

Efficiency measures This analysis seeks to capture efficiency as informational efficiency. For this, we use the *variance ratio* or VR. VR is computed as the ratio of the variance of returns at 10 minutes relative to the variance of returns at 5 minutes (Lo and MacKinlay, 1988). Since a VR of 1 indicates a random walk, we report ($|VR-1|$). Under the null hypothesis of prices following a random walk, the value of $|VR-1|$ should be zero.

A second measure of market efficiency used is the volatility of liquidity in the limit order book. An argument often made against AT is that they present orders to the limit order book, but withdraw these orders before another trader can act on it. Such behaviour in the market implies that we should expect higher volatility of liquidity, when there is higher AT in the market. We use the information from the limit order book to calculate the impact cost as market liquidity, and the standard deviation of the impact cost as the *volatility of liquidity.* We refer to this as LIQRISK.

We calculate the impact cost for two transaction sizes as measures of market liquidity. We then calculate and report the standard deviation of these impact costs ($\sigma_{\mathrm{IC}_{25k}}$ and $\sigma_{\mathrm{IC}_{250k}}$) as measures of market efficiency.

This gives us a total of nine measures of market quality that we use to evaluate the impact of an OTR fee.

4.4 Constructing treated and control samples

We attempt to estimate the causal impact by identifying a treated sample – which are securities effected by the OTR fee, either directly or indirectly – and a control sample, which are similar to the treated securities but which are not affected by the fee. If we are able to identify the treated and control sample appropriately, then we can carry out a difference-in-difference regression with the OTR and market quality as dependent variables on which to measure the impact of the OTR fee. We use a couple of approaches to identify controls that allow estimations with the least endogeneity bias.

Approach 1 : Single stock futures as treated (referred to as SSF) and the underlying equity as control (referred to as Spot(treated)).

The OTR fee in both events are imposed only on the derivatives market. During the period of analysis, the liquid equity derivatives markets at the NSE were the futures markets, both index (Nifty) futures and the SSF. In our analysis, we analyse the impact of the OTR fee on the OTR and market quality of the SSF.

Since there is a strong linkage between the SSF and the underlying equity, this implies that we should be able to use the spot market as a control to measure the impact of the OTR fee. This appears to be an ideal situation because the SSF can be taken as the treated, and it's underlying equity taken as the control since the fee is not directly charged on the orders to trades ratio in the spot market.

However, precisely because of the linkage between the SSF and the spot, the presence of the OTR fee on the futures will effect the spot also. One hypothesis is that higher cost of futures trading will make it more attractive for traders to use the equity spot (Aggarwal and Thomas, 2011). Thus, we expect the liquidity of the spot market to increase, and futures liquidity to simultaneously decrease. Since the derivatives and the spot market are connected by arbitrage, the OTR fee may also effect market efficiency adversely. These reasons lead us to expect an endogeneity bias in our analysis of the impact of the fee on both market liquidity and market efficiency, and will affect our ability to use spot as a control for the futures.

Approach 2 : Equity that have futures as treated (Spot(treated)) and equity without futures as control (Spot(control)).

We attempt to reduce the endogeneity bias described above by using the fact that not all equity shares in the spot market also have futures. The NSE only trades single stock derivatives when the underlying stock satisfy the following eligibility criteria:

1. The stock should be in the top 500 in terms of average daily mar-

ket capitalisation **and** average daily traded value in the previous six months on a rolling basis.

2. The median quarter-sigma order size 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 number of shares held by non-promoters) in the stock should not be less than Rs.3 billion.

We exploit this setting to identify equity shares that are just below the thresholds to satisfy the above criteria. These equity shares without futures becomes the *control* group (called Spot(control)), which match stocks that have futures as the *treated* group (called Spot(treated)).[7]

4.5 Matching methodology

When identifying the set of control stocks in Approach 2, we use a propensity score algorithm which match control and treated stocks on a combination of market capitalisation, prices, floating stock, turnover and number of trades as matching covariates (Davies and Kim, 2009; Aggarwal and Thomas, 2014). The average value of the covariate in the period before the fee is implemented is used as input, and the propensity score is estimated using a logistic regression model (Stuart, 2010). We conduct one-to-one matching on estimated propensity scores for each firm using the nearest neighbor matching algorithm (without replacement) and a caliper of 0.05.

Table 2 presents details of the initial sample and the final sample used in the analysis for both the events. The final sample obtained after matching has 37 treated and 36 control stocks for Event 1, and 47 treated and 45 control stocks for Event 2. Table 3 reports match balance statistics for each event, and shows there is good match balance across all matching covariates between the treated and control firms in the final samples.

4.6 The difference-in-difference specification

For each treated-control group defined previously, we estimate a difference-in-difference (DiD) regression to measure the impact of the fee, using an

[7] The NSE revises the derivatives stocks eligibility every six months. We exclude all stocks from our sample which were dropped from derivatives trading during the period of the analysis.

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

The table gives details of matched sample for both events, 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 sample is the set of stocks with derivatives, and control sample is the set of stocks without derivatives on the NSE platform. Excluded sample indicates that were dropped out of derivatives trading during the sample period.

	Event 1		**Event 2**	
	Initial sample	Final sample	Initial sample	Final sample
Spot(treated)	171	37	201	47
Spot(control)	901	36	1079	45
Excluded	5		7	

approach similar to Friederich and Payne (2015). The DiD is estimated using the following model specification:

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

where, $\text{MEASURE}_{i,t}$ can be any of the OTR for a given stock in the SSF or the spot market and one of the eight market quality measures described in Section 4.3. TREATED_i indicates a dummy variable which takes value 1 for a treated stock, 0 otherwise. FEE_t indicates a time dummy which takes value 1 for the period post the fee imposition, 0 otherwise. The causal impact is measured by $\hat{\beta}_3$ which is the coefficient on $\text{TREATED}_i \times \text{FEE}_t$. $\hat{\beta}_3$ captures the causal impact of the fee on $\text{MEASURE}_{i,t}$. Thus, while Friederich and Payne (2015) examine and comment on $\hat{\beta}_1$, the primary focus is on the significance and the sign of $\hat{\beta}_3$.

In the equation, we also include control variables to account for variation in stocks and the macro-economy. For this, we use stock size ($\text{MCAP}_{i,t}$) and relative tick size measured by the inverse of the stock price for stock variation, and market volatility for the macro-economy, which is measured

Table 3 Match balance statistics for Event 1 and Event 2

The table provides match balance statistics for the matched sample for both the events. 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 treated stocks.
μ_{cr} is the mean for control stocks.
The p-value is reported based on the t-test and Kolmogorov-Smirnov test for equality of mean and distribution respectively.

Panel A: Event 1

	Before matching				After matching			
	μ_{tr}	μ_{cr}	p-value		μ_{tr}	μ_{cr}	p-value	
			t	KS			t	KS
Distance (PS)	0.82	0.03	0.00	0.00	0.51	0.50	0.95	0.96
ln(MCap)	11.38	7.84	0.00	0.00	10.64	10.61	0.52	0.96
ln(Turnover)	5.26	0.12	0.00	0.00	4.14	4.08	0.27	0.36
Floating stock	47.90	45.75	0.00	0.00	45.69	43.83	0.45	0.51
ln(Price)	5.30	4.02	0.00	0.00	5.15	5.26	0.59	0.84
ln(# of trades)	9.46	5.46	0.14	0.03	8.53	8.51	0.65	0.84

Panel B: Event 2

Distance (PS)	0.82	0.03	0.00	0.00	0.51	0.50	0.95	0.96
ln(MCap)	11.38	7.84	0.00	0.00	10.64	10.61	0.52	0.96
ln(Turnover)	5.26	0.12	0.00	0.00	4.14	4.08	0.27	0.36
Floating stock	47.90	45.75	0.00	0.00	45.69	43.83	0.45	0.51
ln(Price)	5.30	4.02	0.00	0.00	5.15	5.26	0.59	0.84
ln(# of trades)	9.46	5.46	0.14	0.03	8.53	8.51	0.65	0.84

as the realized volatility of intraday returns on Nifty index (NIFTY-VOL).

All the variables used in the estimation are winsorised at 99% and 1% level. The reported standard errors are heteroscedasticity consistent, clustered by firm and time.

5 Results

In this section, we present the results of the DiD regressions in Section 4.6 to estimate the causal impact of an OTR fee using the information described in Section 4.1. The results are ordered by the impact of the fee on the OTR itself, and then the causal impact of the fee on the various measures of market quality described in Section 4.3.

5.1 Impact on OTR

The causal impact of the fee on the OTR is measured by the term $\hat{\beta}_3$, which is the coefficient on the interaction term TREATED $\times$ FEE in the following equation:

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

This equation is estimated for both the VWTD OTR and OTR NAIVE as described in Section 4.2. Table 4 presents the estimation results for the Event 1, where the OTR fee was imposed by NSE in 2009. Table 5 presents the estimation results for Event 2 where the OTR fee was imposed by SEBI.

Event 1

From Table 4, we see that $\hat{\beta}_3$ for Event 1 is negative and significant for both the treated-control sample sets. The fee impacted the OTR, not just for the SSF on which it was directly imposed, but also for the underlying equity spot. In both cases, the OTR decreased compared to before the fee was imposed. This implies that the OTR fee was effective and that it had both a direct effect (the SSF) and and indirect effect (on the underlying equity).

Table 4 Difference-in-Difference estimates for impact on the OTR, Event 1

The table reports the results of daily panel DiD estimation for the impact of the OTR fee charged by the exchange (Event 1) on VWTD OTR and OTR NAIVE.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	SSF-Spot(treated)		Spot(treated)-Spot(control)	
	VWTD OTR	OTR NAIVE	VWTD OTR	OTR NAIVE
Fee	**1.06**	**0.58**	**-0.10**	0.0002
	(4.52)	(3.84)	(-4.12)	(0.01)
Treated	**2.13**	**27.16**	**1.53**	0.19
	(5.91)	(17.5)	(13.47)	(1.47)
Treated × Fee	**-1.74**	**-6.04**	**1.18**	**0.33**
	(-5.19)	(-5.03)	(5.27)	(7.14)
Market cap	0.13	-0.41	-0.02	-0.07
	(0.67)	(-0.52)	(-0.4)	(-0.92)
Inverse Price	**0.09**	0.03	0	**-0.03**
	(3.69)	(0.63)	(0.41)	(-3.41)
Market Vol	**-0.05**	0.04	**-0.03**	**0.004**
	(-8.58)	(1.11)	(-6.62)	(-3.07)
R^2	0.25	0.57	0.46	0.15
Treated units	37	37	37	37
Control units	37	37	36	36
# of obs.	7738	7738	8208	8208

Table 5 Difference-in-Difference estimates for impact on the OTR, Event 2

The table reports the results of daily panel DiD estimation for the impact of the OTR fee charged by the regulator (Event 2) on VWTD OTR and OTR NAIVE.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	SSF-Spot(treated)		**Spot(treated)-Spot(control)**	
	VWtd OTR	OTR naive	VWtd OTR	OTR naive
Fee	-0.033	2.826	**0.986**	**1.458**
	(-0.10)	(1.60)	(4.24)	(3.21)
Treated	**-4.867**	**90.943**	**6.302**	2.978
	(-5.66)	(5.26)	(7.16)	(1.75)
Treated × Fee	-0.106	**31.504**	**-0.929**	0.098
	(-0.29)	(2.63)	(-2.34)	(0.12)
Market cap	-0.161	4.533	-0.351	0.784
	(-0.47)	(0.88)	(-1.07)	(1.40)
Inverse Price	**-0.093**	**-1.119**	**-0.113**	**-0.221**
	(-3.06)	(-2.51)	(-4.08)	(-3.41)
Market Vol	0.007	0.291	0.014	-0.030
	(1.16)	(0.65)	(1.24)	(-1.81)
R^2	0.19	0.13	0.25	0.13
Treated units	47	47	47	47
Control units	47	47	45	45
# of obs.	9030	9030	10233	10233

This analysis suggests that the OTR fee imposed by the NSE was effective in reducing the OTR. We next analyse the impact of the OTR fee on market quality, which includes liquidity and market efficiency.

Event 2

We now analyse the impact of the fee when it was introduced by SEBI in July 2012. Unlike the 2009 event, SEBI directed that the fee was only to be levied on *algorithmic* orders with certain exemptions as described in Section 3.

Table 6 Percentage of order events beyond 1 percent price limit

The table presents the mean and median values of percentage of order events that breached the 1 percent price limit.
Columns 2 and 3 represent the values for matched treated stocks on the SSF market, Columns 5 and 6 represent the values for matched treated stocks on the spot market, and Columns 8 and 9 represent the values for matched control stocks on the spot market.
The table also shows the p-values based on the t-test for the difference in the pre- and post-event values.

	SSF			**Spot**(treated)			**Spot**(control)		
	Pre	Post	p-value	Pre	Post	p-value	Pre	Post	p-value
Mean	27.37	18.72	0.00	29.15	25.90	0.21	19.72	19.04	0.72
Median	26.41	16.75	0.00	28.67	25.43	0.22	18.73	18.33	0.84

Table 5 shows the impact of the fee in Event 2 on the VWTD OTR and OTR NAIVE. Relative to the underlying stocks on the spot market, the positive and significant coefficient with 'Treated' dummy on OTR naive indicates that the OTR on the SSF market is significantly higher than the OTR on the spot market, while the VWTD OTR shows no significant change. The table also reports the estimates from the Spot-spot regression. The coefficient on the interaction term between Treated and Fee shows a negative and significant coefficient for the VWTD OTR and an insignificant value for OTR naive. This suggests that the OTR on the spot with the SSF dropped after the fee was imposed on the related SSF.

These results suggest that the fee imposed in Event 2 had the effect of *increasing* the OTR on the SSF. This is counter to the expected outcome from increasing cost to higher frequency trading. Since the fee was imposed in an asymmetric manner across orders in the book, we surmise that traders reduced orders where the fee is binding while increasing orders where the fee is not binding. We examine the percentage of orders beyond 1 percent before and after the fee was imposed for our matched sample, and present the results in Table 6.

The results indicate a significant *reduction* in the percentage of orders placed beyond 1 percent price limit for the SSF contracts on treated stocks. The average dropped from 27% in the pre-event period to 18% in the post-event period. This indicates that there was some impact of the fee on the orders placed beyond the 1% price limit on the SSF market. We do not see a similar effect on the underlying market for the matched treated stocks, nor on the matched control stocks. The decline in the percentage of orders beyond the 1 percent price limit could have an implication for the overall depth of the market, and the liquidity far away from the touch.

5.2 Impact on liquidity

The causal impact of the fee on market liquidity is estimated using the equation:

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

where the liquidity measures are QSPREAD, two impact cost measures, two values of the depth of the limit order book, and the Amihud illiquidity ratio (ILLIQ).

The two impact cost measures are IC_{25k} and IC_{250k} which are the price impact for trading Rs.25,000 and Rs.250,000 respectively of the treated set. During the period of the analysis, the minimum lot size of a trade of the SSF was Rs.250,000. So, while we can calculate IC_{25k} and IC_{250k} for the underlying spot, we can only calculate IC_{250k} for the SSF.

The two depth measures are TOP1DEPTH and TOP5DEPTH for the rupee value of the amount available to trade at the depth of one price in the limit order book and at the depth of five prices in the limit order book respectively.

Table 7 presents the DiD results for the effect of the OTR fee on the above six liquidity variables for Event 1, while Table 8 presents the DiD results for Event 2.

Event 1

The results show that there is a significant negative impact of the OTR fee on the liquidity measures of the SSF market relative to the underlying spot for those measures that capture transactions costs: QSPREAD, IC_{25k} and IC_{250k}

Table 7 Difference-in-Difference estimates for impact on market liquidity, Event 1

The table reports the results of daily panel DiD estimations on six liquidity related variables – QSPREAD, IC_{25k} and IC_{250k}, TOP1DEPTH, TOP5DEPTH and ILLIQ for Event 1. The table presents the results for both treated and controls sets separately in Panel A and Panel B.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	QSPREAD	IC_{25k}	IC_{250k}	TOP1DEPTH	TOP5DEPTH	ILLIQ
Panel A: SSF-Spot(Treated)						
Fee	**0.005**	0.002	-0.009	**0.108**	**0.125**	0
	(2.24)	(0.62)	(-1.90)	(3.04)	(2.99)	(0.28)
Treated	**0.141**	**0.121**	**0.046**	**1.444**	**1.237**	0
	(11.26)	(9.74)	(3.47)	(17.06)	(15.24)	(2.23)
Treated × Fee	**-0.05**	**-0.05**	**-0.04**	-0.055	-0.06225	**0**
	(-6.87)	(-6.17)	(-4.11)	(-1.16)	(-1.03)	(-4.04)
Market Cap	-0.01	-0.01	**-0.03**	**0.23**	**0.23**	**-0**
	(-1.26)	(-1.70)	(-3.14)	(3.87)	(4.09)	(-2.67)
Inverse Price	**-0.001**	**-0.002**	**-0.002**	**0.036**	**0.046**	0
	(-2.26)	(-2.94)	(-3.68)	(5.41)	(8.27)	(-1.83)
Market Vol	**0.003**	**0.003**	**0.004**	**-0.014**	**-0.016**	**0**
	(9.0)	(10.64)	(15.90)	(-10.57)	(-10.57)	(9.44)
R^2	0.53	0.48	0.29	0.76	0.73	0.1
Treated units	37	37	37	37	37	37
Control units	37	37	37	37	37	37
# of obs	7738	7738	7738	7738	7738	7738
Panel B: Spot(Treated)-Spot(Control)						
Fee	0.001	0.001	-0.004	-0.019	0.006	0
	(0.14)	(0.01)	(-0.20)	(-0.51)	(0.14)	(0.70)
Treated	-0.022	-0.034	**-0.088**	**0.432**	**0.429**	0
	(-1.27)	(-1.61)	(-2.66)	(5.11)	(5.01)	(-1.43)
Treated × Fee	-0.002	-0.002	-0.001	**0.123**	0.112	0
	(-0.40)	(-0.29)	(-0.04)	(2.29)	(1.89)	(-0.60)
Market cap	-0.012	-0.018	-0.039	**0.148**	**0.150**	0
	(-0.91)	(-1.14)	(-1.44)	(2.47)	(2.42)	(-1.09)
Inverse Price	-0.001	-0.002	-0.003	**0.044**	**0.050**	0
	(-0.84)	(-1.00)	(-0.89)	(6.08)	(7.54736)	(-1.01)
Market Vol	**0.001**	**0.002**	**0.005**	**-0.018**	**-0.020**	0
	(7.22)	(8.62)	(9.35)	(-11.58)	(-11.16)	(4.58)
R^2	0.03	0.05	0.08	0.46	0.48	0.03
Treated units	37	37	37	37	37	37
Control units	36	36	36	36	36	36
# of obs	8208	8208	8193	8208	8208	8207

and ILLIQ. For this treated-control pair, the impact of the OTR fee is negative but insignificant for the limit order book measures and ILLIQ. However, there is only one liquidity measure which has a significant value of $\hat{\beta}_3$ which is the TOP1DEPTH measure. If we focus on the estimated coefficients that are significant, the evidence suggests that the OTR fee *improved* the transactions costs after the fee was imposed. It implies that when the OTR fee was imposed, transaction costs on the SSF market *decreased* relative to the underlying equity stocks. There does not appear to be a significant impact on market liquidity measured by the order book depth.

These results appear only as a direct effect, because the results are significant (mostly) only for the SSF as treated compared with the underlying spot as control. There does not appear to be strong results for Spot(treated) compared to Spot(control), which suggests that there are little indirect effects of the OTR fee in Event 1.

Event 2

Table 8 presents the DiD results of the impact of the OTR fee imposed by SEBI (Event 2) on liquidity. We observe that the $\hat{\beta}_3$ term is insignificant for all measures except for the inside depth (TOP1DEPTH) for SSF relative to the underlying equity spot, which is also the same result in the estimation which uses the underlying equity spot with futures as the treated and the spot without futures as the control.

Table 8 Difference-in-Difference estimates for impact on market liquidity, Event 2

The table reports the results of daily panel DiD estimations on six liquidity related variables – QSPREAD, IC_{25k} and IC_{250k}, TOP1DEPTH, TOP5DEPTH and ILLIQ for Event . The table presents the results for both treated and controls sets separately in Panel A and Panel B.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	QSpread	IC_{25k}	IC_{250k}	Top1depth	Top5depth	illiq
Panel A: SSF-Spot(treated)						
Fee	**-0.003**	**-0.006**	**-0.023**	**0.137**	**0.123**	**0**
	(-2.068)	(-2.734)	(-3.636)	(3.372)	(2.779)	(-2.058)
Treated	**0.127**	**0.102**	0.003	**1.779**	**1.445**	0
	(7.380)	(5.777)	(0.128)	(18.773)	(15.220)	(0.780)
Treated × Fee	-0.004	-0.001	0.017	**-0.133**	-0.094	0
	(-0.494)	(-0.110)	(1.654)	(-2.623)	(-1.714)	(1.764)
Market cap	0.001	-0.002	-0.015	**0.190**	**0.174**	0
	(0.164)	(-0.327)	(-1.786)	(2.907)	(2.522)	(0.292)
Inverse Price	**0.001**	**0.001**	**0.002**	**0.028**	**0.027**	0
	(2.567)	(2.508)	(2.461)	(6.221)	(5.980)	(1.811)
Market Vol	**0.001**	**0.001**	**0.002**	**-0.004**	**-0.005**	**0**
	(5.425)	(6.009)	(7.594)	(-5.282)	(-6.653)	(3.182)
R^2	0.32	0.24	0.09	0.71	0.62	0.02
Treated	47	47	47	47	47	47
Control units	47	47	47	47	47	47
# of obs.	9030	9030	9030	9030	9030	9030
Panel B: Spot(treated)-Spot(control)						
Fee	-0.005	-0.007	-0.021	0.059	0.068	0
	(-1.080)	(-1.115)	(-1.401)	(1.485)	(1.747)	(-0.462)
Treated	-0.008	**-0.018**	**-0.052**	**0.367**	**0.386**	**0**
	(-1.731)	(-2.209)	(-2.417)	(3.504)	(3.531)	(-2.166)
Treated × Fee	0	0	0	0.054	0.036	0
	(0.037)	(0.067)	(0.003)	(0.959)	(0.609)	(-0.184)
Market cap	-0.001	**-0.007**	**-0.027**	**0.186**	**0.156**	**0**
	(-0.237)	(-2.164)	(-3.493)	(2.822)	(2.254)	(-2.466)
Inverse Price	**0.002**	**0.001**	**0.002**	**0.041**	**0.036**	0
	(9.804)	(7.614)	(2.161)	(7.927)	(6.975)	(1.517)
Market Vol	**0.001**	**0.001**	**0.002**	**-0.007**	**-0.007**	**0**
	(8.715)	(9.548)	(9.010)	(-5.869)	(-5.840)	(2.756)
R^2	0.380	0.230	0.160	0.490	0.420	0.060
Treated units	47	47	47	47	47	47
Control units	45	45	45	45	45	45
# of obs.	10233	10233	10223	10233	10233	10233

5.3 Impact on efficiency

The causal impact of the fee on market efficiency is estimated using the equation:

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

where the efficiency measures are variance ratio and the standard deviation of the impact cost measures. As described in the previous section on liquidity measures, the two impact cost measures are IC_{25k} and IC_{250k}. We calculate the variance of these as measures of efficiency – the lower the variance, the more efficient the price process. This gives us the following three market efficiency measures: VR-1, $\sigma_{\text{IC}_{25k}}$ and $\sigma_{\text{IC}_{250k}}$. The details of these measures are described in Section 4.3.

We also present the response of the returns volatility to the OTR fee to set the context of the macro-economic behaviour in the pre-OTR and the post-OTR fee period for the treated and control samples. This is represented as σ_r in the results.

Table 9 presents the DiD results for the effect of the OTR fee on the above three efficiency measures for OTR fee Event 1, and Table 10 presents the estimation results for OTR fee Event 2.

Event 1

We find that there are significant and negative values for the $\hat{\beta}_3$ coefficient in the case of liquidity risk of the SSF relative to the underlying equity shares as control. This suggests that the liquidity risk improved as the impact of the OTR fee in Event 1. However, there is no such effect in the case of the liquidity risk of Spot(treated) which has futures, relative to Spot(control) which does not. There does not appear to be any improvement in the informational efficiency measure, $|VR - 1|$ in either case.

The estimated values of $\hat{\beta}_3$ on σ_{SSF} vs. $\sigma_{\text{SPOT(TREATED)}}$ suggests that the returns volatility of the SSF relative to the underlying equity spot saw a significant decrease before and after the OTR fee was imposed. We also see that there is a significant and positive value of the coefficient on $\sigma_{\text{SPOT(TREATED)}}$ vs.

Table 9 Difference-in-Difference estimates for impact on efficiency, Event 1

The table reports the results of daily panel DiD estimations on three efficiency variables – $\sigma_{\text{IC},25k}$, $\sigma_{\text{IC},250k}$ and $|VR - 1|$ for Event 1, along with σ_r as a measure of sample volatility. The table presents the results for both treated and controls sets separately in Panel A and Panel B.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	σ_r	$\sigma_{\text{IC},25k}$	$\sigma_{\text{IC},250k}$	$\|VR-1\|$
Panel A: SSF-Spot(Treated)				
Fee	-0.858	-0.004	-0.010	-0.008
	(-0.97)	(-0.98)	(-1.67)	(-1.49)
Treated	**16.094**	**0.084**	**0.038**	**0.028**
	(7.61)	(6.53)	(2.81)	(3.15)
Treated × Fee	**-6.038**	**-0.052**	**-0.043**	-0.005
	(-3.80)	(-5.72)	(-4.26)	(-0.64)
Market Cap	**-3.238**	-0.009	-0.011	-0.002
	(-3.22)	(-1.27)	(-1.39)	(-0.48)
Inverse Price	-0.004	**-0.003**	**-0.003**	-0.001
	(-0.05)	(-5.56)	(-6.04)	(-1.91)
Market Vol	**1.310**	**0.002**	**0.003**	**-0.002**
	(25.91)	(10.12)	(12.74)	(-7.23)
R^2	0.35	0.27	0.19	0.02
Treated units	37	37	37	37
Control units	37	37	37	37
# of obs	7738	7738	7738	7730
Panel B: Spot(treated)-Spot(control)				
Fee	**-5.027**	0.018	0.003	0.001
	(-3.49)	(0.76)	(0.31)	(0.29)
Treated	**-10.071**	-0.029	-0.026	-0.011
	(-5.35)	(-1.12)	(-1.45)	(-1.22)
Treated × Fee	**4.157**	-0.025	-0.012	-0.008
	(2.47)	(-1.02)	(-1.02)	(-1.13)
Market cap	**-3.860**	-0.027	-0.016	0
	(-3.01)	(-1.10)	(-1.25)	(0.00)
Inverse Price	0.004	-0.004	-0.003	-0.001
	(0.02)	(-1.52)	(-2.27)	(-1.63)
Market Vol	**1.289**	**0.001**	**0.003**	**-0.001**
	(26.73)	(4.96)	(8.95)	(-5.19)
R^2	0.24	0.040	0.07	0.01
Treated units	37	37	37	37
Control units	36	36	36	36
# of obs	8203	8208	8192	8135

$\sigma_{\text{SPOT(CONTROL)}}$. Taken together, the results suggests that there is an *increase* in the volatility of equity shares on which futures are traded as a result of the OTR fee. While it appears that there is a *decrease* in the volatility of futures, there is an *increase* in the volatility of the underlying spot returns. Furthermore, this increase in volatility cannot be attributed to increased liquidity risk which decreased for the futures and did not change for the spot.

Event 2

Table 10 presents the causal impact of the Event 2 OTR fee on the efficiency measure. The $\hat{\beta}_3$ in this estimation show a similar result for changes in the variance ratio, which is negative and insignificant at 95%. This changes if we consider the results at a 90% confidence interval, at which stage the coefficient does become negative and significant, suggesting that the fee *worsened* informational efficiency of the futures relative to the underlying equity spot.

The estimated coefficients do show a significant *increase* in the liquidity risk of the futures relative to the underlying equity spot as the impact of the Event 2 OTR fee. The worsening liquidity risk is also seen for the stocks that have futures trading relative to those without, but only for the larger size transactions. This suggests that traders are moving away from placing orders that support larger sized trades in either futures or in the stocks that have futures trading relative to those stocks that do not have futures trading.

These results do not bode well from the usual perspective of a regulatory intervention that seeks to improve market quality and market stability. In the case of this (Event 2) fee, the analysis shows that the OTR fee has not affected the OTR and worse, appears to be adversely impacting the quality of both the liquidity and the liquidity risk of the market.

5.4 Summary

At the end of the analysis, we re-visit the three questions posed in Section 3 to understand the efficacy of a fee charged based on the OTR as an intervention against high frequency trading.

Q1: Does the OTR fee have the intended impact of a lower value for the OTR itself?

We find that the OTR fee in Event 1 was successful in reducing the OTR (Table 4. The fee was charged without exception to all orders and all participants in

Table 10 Difference-in-Difference estimates for impact on efficiency, Event 2

The table reports the results of daily panel DiD estimations on three efficiency variables – $\sigma_{\text{IC},25k}$, $\sigma_{\text{IC},250k}$ and $|VR-1|$ for Event 1, along with σ_r as a measure of sample volatility. The table presents the results for both treated and controls sets separately in Panel A and Panel B.
'Fee' is the dummy differentiating treated and control, while 'Treated' is the dummy which differentiates the pre-OTR fee and post-OTR fee periods. 'Treated × Fee' is the interaction term which captures the causal effect of the fee on the OTR for the treated sample.
Standard errors are heteroscedasticity consistent, clustered at the firm and time level. **Boldface** values indicate significance at 5%.

	σ_r	$\sigma_{\text{IC},25k}$	$\sigma_{\text{IC},250k}$	$\|VR-1\|$
Panel A: SSF-Spot(treated)				
Fee	**-2.005**	-0.003	-0.006	0.004
	-3.014	-1.132	-1.306	1.161
Treated	**22.623**	**0.070**	0.013	**0.037**
	10.141	4.397	0.733	3.496
Treated × Fee	**-6.066**	**0.017**	**0.022**	-0.014
	-3.185	2.017	2.297	-1.561
Market cap	**-2.701**	0.005	0.004	**0.018**
	-4.425	0.619	0.528	3.307
Inverse Price	**0.361**	0.000	0.000	0.001
	6.682	1.005	0.817	1.696
Market Vol	**0.219**	**0.001**	**0.001**	0.000
	4.878	3.874	4.443	-1.168
R^2	0.30	0.15	0.02	0.03
Treated units	47	47	47	47
Control units	47	47	47	47
# of obs.	8964	9030	9030	8782
Panel B: Spot(treated)-Spot(control)				
Fee	0.654	-0.008	**-0.033**	-0.007
	0.659	-1.469	-3.528	-1.124
Treated	**-3.239**	**-0.017**	**-0.042**	**-0.025**
	-2.266	-2.000	-2.240	-2.777
Treated × Fee	**-2.355**	0.005	**0.029**	0.012
	-1.996	0.823	2.796	1.637
Market cap	**-3.178**	-0.002	-0.002	**0.011**
	-4.670	-0.726	-0.319	2.552
Inverse Price	**0.298**	0.000	0.000	**0.001**
	5.954	0.817	0.326	2.236
Market Vol	**0.446**	**0.001**	**0.001**	**-0.001**
	10.500	6.329	5.042	-3.085
R^2	0.22	0.04	0.03	0.02
Treated units	47	47	47	47
Control units	45	45	45	45
# of obs.	10233	10233	10218	10226

the equity derivatives markets. The observed result was that the fee reduced the OTR both directly (on the SSF market relative to the underlying equity spot) and indirectly (on the underlying equity spot with futures relative to equity spot without futures). The OTR fee was imposed by the NSE with the objective to deter traders from sending unproductive orders into the SSF market, and to better manage challenges to access bandwidth to the trading system. We also observe that this objective was achieved without causing much damage to the market.

However, the results are ambiguous for the fee imposed in Event 2 (Table 5. The fee was charged for a limited range of the orders that were placed away from the touch, and was not applicable to market makers. We see that across the four OTR measures, only two out of four estimations deliver significant results. Further, the results indicate that there is an INCREASE in the OTR for the futures. In part, this is a problem with a much smaller sample set that may pose a challenge in achieving sound inference. In part, the results may be in indicating a higher OTR for the orders at the touch, since these were not eligible to be counted for the fee. Further analysis is required that differentiates the behaviour of orders to trades at the touch, as opposed to the average orders against trades across the full limit order book to test and establish this hypothesis for Event 2.

The next set of questions raised asked about the impact of the fee on the market quality where quality is measured by liquidity and efficiency.

Q2: What were the consequence of the fee on market liquidity?

The impact of the fee on market liquidity is relatively clear in the case of Event 1. The analysis show that the fee has led to a statistically significant decrease in the trading costs measured by QSPREAD, IC_{25k} and IC_{250k} of the futures relative to their underlying equity spot. There is no clear result about the orders in the limit order book, except for an increase in the orders at the touch in limit order book for the equity shares that trade futures relative to those that do not. On average, we infer that liquidity *improved* when the exchange imposed the fee on OTR.

Given that the results about the impact of the fee in Event 2 is ambiguous, it appears consistent that the analysis indicates practically no effect on market liquidity as a consequence of the fee imposed by the regulator.

Q3: What were the consequence of the fee on market efficiency?

The impact of the fee on market efficiency for Event 1 shows that there is no significant change in informational efficiency (in the results on the variance ratio of returns). But there is a significant *decrease* in the liquidity risk of the futures relative to the underlying equity spot.

In the case of Event 2, the results are similar for no change in the information efficiency. However, the results show an *increase* in liquidity risk in the futures relative to the underlying equity spot. This runs counter to what we might expect as the objective of the regulator in impeding high frequency trading. These results are consistent whether we consider the direct effect of the fee (in the behaviour of the futures relative to the underlying equity) or even the indirect effect of the fee (in the behaviour of the stocks with futures relative to stocks without futures). More damaging is the result about worsening of liquidity risk for larger sized orders that suggests that the OTR fee in Event 2 appears to have an asymmetric adverse impact on quality of the market for larger sized trades compared to smaller sized ones.

These answers appear to indicate that OTR fee imposed in Event 1 had a significant impact compared to the fee imposed in Event 2. The fee of Event 1 had the effect of reducing the overall average OTR, reducing the transactions costs in the futures relative to the underlying equity spot, and reduced the liquidity risk in the futures relative to the underlying equity spot. The fee of Event 2 had no impact in reducing the overall average OTR, no impact on market liquidity but increased the liquidity risk of the futures relative to the underlying equity spot.

6 Conclusion

Over the world, financial market regulators have mandated the use of a fee as a mechanism targeted to managing what was considered excessive trading. These interventions have been increasingly observed as trading on financial markets have become increasingly driven by algorithms. This paper uses a unique opportunity to study how such regulatory interventions cause changes in order placement and trading patterns as well as changes in overall market quality. The opportunity is found in two events that took place in the Indian equity market as a response to the growth of algorithmic trading intensity, when the OTR fee was used to control inadvertent, adverse effects of algorithmic trading on the markets. The first use was by the exchange to manage bandwidth load and the second came later when the regulator imposed the fee in the public interest.

This is a unique opportunity because the two events are cleanly separated so that each event can be cleanly analysed within the same market microstructure. Further, the markets observed are liquid enough and the OTR fee applied in such a manner that a set of treated and control samples can be constructed to help a causal analysis of the impact of the fee.

The analysis suggests that the exchange initiated OTR fee, with an explicit objective, was effective while there is ambiguity in impact of the fee imposed by the regulator. The OTR decreased on average when the exchange imposed the fee, while a similar, simple examination suggests that the OTR *increased* on average when the regulator imposed the fee. This runs counter to the apparent objective of the intervention. Only a more detailed empirical analysis suggests that there was a differential impact of the fee at various parts of the limit order book.

What the results suggest is that it is not just the intervention, but the clarity of the objective for which it is applied and the resultant form that is important in delivering the outcomes of the intervention. In the case of the exchange intervention which was used as a disincentive to spurious order flow, there was an overall reduction of the OTR *and* an improvement in the liquidity and efficiency of the futures, with lower impact cost of the trade and lower volatility of the impact cost across trade executions. These are clearly observed in the overall average values for the market. On the other hand, there is ambiguity in the impact of the fee imposed by the regulator. The change in the OTR is opposite to what appeared to be desired (increase opposed to decrease) and there is no visible change or evidence of improvement of the overall liquidity and efficiency in the market after the fee is imposed.

If the objective of the regulator in imposing the OTR fee was in the public interest, then the evidence about the impact on the OTR or market quality is not likely to boost investor confidence in the market. Instead, an intervention in the public interest should benefit from visible results using simple, default analysis. Thus, this paper thus presents a cautionary tale in regulators intervening in market design: optimal outcomes appear to be best guided with clear and focussed objectives. The analysis suggests that the expected outcomes should be part of the stated objective and design of a market intervention.

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