Does Trade Size Restriction Affect Trading Behavior? - Evidence from Indian Single Stock Futures Market

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Abstract

Algorithmic (algo) traders use their advantage of speed to execute a large number of small-sized trades in a very short time. In the presence of minimum trading unit (MTU) restriction, we find that they are forced to trade at the smallest possible sizes - the MTU. Using a novel dataset of single stock futures market obtained from National Stock Exchange (NSE) of India, we show that MTU restriction effectively dictates trade sizes of more than two-thirds of the trades, where at least one of the parties is an algo trader. We also inspect the impact of an upward revision in minimum contract size on trading behavior in the Indian market during 2015. We find that algo traders still continue to trade at the minimum possible sizes, but the difference in trade sizes between algo and non-algo trades reduce due to the revision. Overall traded volume seems to be largely unaffected by the contract size revision. However, we do observe a significant negative shock on due to the announcement of contract size revision on traded volume.

1 Introduction

Exchanges all over the world often impose a restriction on the minimum size of a trade. This restriction can be either imposed by explicitly specifying the minimum trading unit (MTU) for a security or by specifying the minimum size of a traded contract. Specification of MTU or minimum contract

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size is an intriguing question as it requires a consideration of trade-off between transaction cost and volume (Karagozoglu & Martell, 1999). While lower contract size can increase the transaction cost, higher contract size may force out certain market participants. In the absence of any trade size restrictions, traders are faced with an exercise to choose optimum trade size that balances between impact cost and transaction cost. Existing academic literature primarily focuses on the reduction in contract size or MTU (Karagozoglu & Martell, 1999; Karagozoglu, Martell, & Wang, 2003) and its impact on increased liquidity in terms of traded volume or reduced bid-ask spread and vice-versa. Reduction in MTU (Amihud, Mendelson, & Uno, 1999; Hauser & Lauterbach, 2003a) is seen to increase the number of individual shareholders and appreciation in share price, which is consistent with Merton (1987). However, we do not find any empirical study relating trade size restriction to trading behavior.

This paper tries to look into how the trading behavior of various market participants, especially algorithmic traders is affected in a market with trade size restrictions. Algorithmic traders gain competitive advantage through their ability to execute a large number of small-sized trades in a small period. We base our analysis on the Indian derivatives market for single stock futures (SSF). We also use a natural experiment scenario provided by the upward revision of minimum contract size as proposed by the Indian capital market regulator SEBI (Securities and Exchange Board of India) in 2015, to observe how market participants react to such exogenous shocks. With the introduction of de-materialized trading in the equity market in 1999, most of the trading in the Indian equity market at present is carried out in the paperless format with no concept of minimum trading unit (MTU) or minimum contract size. In the derivatives segment, however, the concept of trading in lots is still in vogue where the lot sizes are specific to an underlying security. We also look at how a market-wide upward revision of contract size revision affects traded volume in the SSF market.

With the introduction of algorithmic trading in various exchanges, presently a significant proportion of trades are initiated automatically from computer terminals without any real-time manual intervention. This paradigm shift in trading mechanism has led traders to adopt appropriate trading strategies to minimize impact costs. Over the last decade and a half, the average trade size in exchanges over the globe has significantly reduced [1] (Angel, Harris, & Spatt, 2011; O'Hara, Yao, & Ye, 2014), owing much of it to the increase in algorithmic trading activity. Traders often face the challenge to choose optimum trade sizes with the objective of reducing overall impact cost and transaction cost (Bertsimas & Lo, 1998), especially when faced with the problem of buying or selling a pre-defined quantity. Impact cost

[1] Securities and Exchange Commission (SEC) release 34-61358, 2010

is specified as the Algorithmic traders use their advantage of speed to split a larger order into smaller segments so that the price impact is lowest. They are more likely to carry out a number of small trades throughout the day rather than a few bulk trades. Algo traders are also mostly intra-day traders who would rarely carry over their positions. In this context, it may not be wise to assume that events such as contract size revision will affect all trader groups (algo vs. non-algo) uniformly.

Our work tries to bring together the existing strands of literature on algorithmic trading and minimum contract size. We look at how minimum contract size specification affects trading strategy for algorithmic traders vis-a-vis non-algorithmic traders. We also observe how the phenomenon of contract size revision affected trading behavior for various trader groups. Using a novel intra-day dataset obtained from the National Stock Exchange (NSE), we can decompose the trading data for different trader groups namely proprietary, custodians and non-proprietary non-custodians (NCNP) traders and also identify trades that were automatically generated from algorithmic trading terminals. We also observe that algorithmic traders try to trade at the smallest possible trade sizes, often limited by the MTU. Institutional investors, who have been known to trade on information, are observed to trade at relatively larger trade sizes while not using algorithms to execute their trades. While using algorithms, their trade sizes are significantly reduced.

The announcement by the regulator SEBI to increase minimum contract size had created a lot of hue and cry in the market speculating that this move could force out retail traders from the market [2] [3]. Considering that retail traders contribute a significant proportion of the traded volume in the SSF market, that could have translated to a significant reduction in overall traded volume.

The contribution of this paper to the existing literature is threefold. First, we find that in a particular trade, if one of the parties (buyer or seller) is algorithmic in nature, the trade size is most likely to the dictated by that trader. Next, we show that minimum trading unit restriction refrain market participants, especially algorithmic traders from optimizing their trade sizes and forces them to trade at the minimum specified trade size. Lastly, we show that unlike the impact of MTU reduction that most certainly improves liquidity, the converse is not always true. The upward revision of the minimum size of derivative contracts in NSE SSF market had no significant impact on traded volume in contradiction to market expectations. We do find a transitory negative shock immediately after the announcement by

[2]http://economictimes.indiatimes.com/markets/stocks/news/increase-in-futures-lot-size-may-shut-out-retail-investors/articleshow/48430033.cms

[3]http://economictimes.indiatimes.com/markets/stocks/news/lot-size-revision-in-fo-puts-small-traders-in-a-spot/articleshow/49105221.cms

SEBI followed a subsequent positive correction.

The rest of the paper is arranged as follows - in the next section, we talk about the institutional setting of the Indian derivatives market and the revision in contract size. We also discuss the paradoxical growth of the NSE SSF market. In the following, section we discuss the existing literature on lot size revision and algorithmic trading. We also discuss our dataset and variables used for analysis. In the analysis section, we separately study how MTU restriction impacts algo trading behavior, how algo trading behavior changes in response to MTU revision and what happens to the overall traded volume due to the revision.

2 Institutional Setting

2.1 Derivatives Trading in NSE

Derivatives trading was first introduced in India by National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) in 2000. First products to be introduced were index futures, followed by index options, options in individual stocks and futures in single stocks. Since then, trading in derivatives has seen a phenomenal growth in India. National Stock Exchange, set up in 1992 has surpassed the incumbent BSE (established in 1875) in terms of traded volume.

At present, NSE has the largest share of equity as well as derivative market activities in India. Globally NSE ranks as one of the largest exchange in terms of number of contracts traded and notional turnover, both in single stocks category as well as indices. Presently NSE is the second largest exchange in the single stock futures segment both in terms of notional turnover and number of contracts traded.[4] The statistics are equally impressive for other segments also. NSE is a completely order driven market which operates on a strict price-time priority. There is no traditional market maker or specialist in the trading system. NSE trading hours is from 9:15 AM IST (GMT+5:30) in the morning to 3:30 PM IST with no breaks in between.

2.2 Algorithmic Trading

On April 2008, the market regulator SEBI started allowing Direct Market Access (DMA) facility to the investors that allowed them to directly access the exchange trading system through the broker's infrastructure but without the manual intervention of the broker. This particular provision is

[4] Source: World federation of Exchanges Database (Dec 2015) - www.world-exchanges.org

considered the first stepping stone for algorithmic trading in the Indian securities market. In 2010, NSE introduced co-location facility that enabled traders to place their servers at the exchange premises, a move that certainly helped algorithmic traders. Further, in November 2012, the charge to avail co-location facility was cut to almost in half. Post-2012, we have seen an exponential growth in algo trading.

2.3 Contract Size Revision

Till 2015, SEBI had specified the minimum contract size for trading in derivative securities at INR 2 lacs [5]. The minimum lot sizes or MTU for different securities were derived accordingly. SEBI in its July 2015 circular revised the minimum contract size for derivative securities from INR 2 lacs (0.2 million) to INR 5 lacs (0.5 million) in notional value [6]. Because of the increased contract value, and hence the need for higher margins, it was expected that small investors might be forced to shift from trading in stock futures to trading in options which is perceived to be riskier.

2.4 NSE & The SSF Market Paradox

Unlike many other developed markets, NSE futures market has shown incredible progress since its inception. Part of it can be attributed to lack of a stock-lending market and also restrictions on short-selling in the equity market [7]. SSFs, being linear payoff products, is extremely popular among the retail traders who find it easier to estimate their pay-offs.

Using NSE data for estimating the impact of contract size revision provides a number of advantages. Apart from being one of the largest exchanges for trading in SSF market, it also captures a significant proportion of trading activity in India. Unlike other large exchanges over the globe, NSE represents a largest un-fragmented capital market in one of the largest economies in the world.

In the Indian context, trading in Single Stock Futures started in NSE as early as November 2001. The Securities Lending and Borrowing (SLB) scheme, however, was launched much later in April 2008. Since then in spite of the tremendous growth of the Single Stock Futures market, the SLB market has not witnessed similar growth pattern. Existing literature argues that two functioning markets (equity and SSF market in this case) together can act as a redundancy for the third related market (SLB market

[5]one lac is equivalent to one tenth of a million

[6]SEBI Circular No. CIR/MRD/DP/14/2015 dated 13th July 2015

[7]SEBI banned short-selling in the equity market in March 2001. Only retail investors were allowed to short-sell. In early 2008, the restriction was revoked for institutional traders (like mutual funds) and they were allowed to trade under modified guidelines.

in this case) (Kumar & Tse, 2009). In such cases, the market introduced later is less likely to grow at par with the incumbent markets.

Table 1: Market Growth Statistics for Spot Market, SLB Market, and SSF Market

Market Turnover (in INR Cr)			
Year	**Security Lending Borrowing**	**Cash/Spot Market**	**Single Stock Futures**
2008-2009	0.01	2,752,023	3,479,642
2009-2010	0.07	4,138,024	5,195,247
2010-2011	1.11	3,577,412	5,495,757
2011-2012	7.38	2,810,893	4,074,671
2012-2013	16.34	2,708,279	4,223,872
2013-2014	13.28	2,808,488	4,949,282
2014-2015	11.41	4,329,655	8,291,766
2015-2016	29.58	4,236,983	7,828,606

3 Literature Review

Existing studies have looked primarily into the impact of reducing minimum trading unit or minimum contracts size specification on market liquidity. It was that reduction of MTU in the equity market leads to increase in the number of individual shareholders (Amihud et al., 1999; Hauser & Lauterbach, 2003b; Ahn, 2014; Isaka, 2014). It has also been reported that reduction in MTU leads to an appreciation in share prices, not only in the short run(Amihud et al., 1999) but also in the long run (Isaka, 2014). Complete reduction of MTU to one unit similarly results in improving liquidity (Gozluklu, Perotti, Rindi, & Fredella, 2015). The improvement in liquidity is often due to the reduction in adverse selection. In the derivatives market, we observe similar results. Karagozoglu and Martell (1999) provide the unique example of both simultaneous upward and downward revision of contract sizes to demonstrate how MTU reduction improves liquidity while increasing contract size does the reverse, though the empirical evidence are not as strong as that for contract size reduction. Bjursell, Frino, Tse, and Wang (2010) report that an increase (decrease) in contract size increases (decreases) trading frequency as well as daily price volatility.

Splitting of index futures contract is also deemed to have a similar impact as a reduction of the MTUs. Huang and Stoll (1998) predict that reduction in S&P 500 futures contract may attract new smaller investors. They also predict that it would also help existing larger investors by providing them an option to fine tune their hedges and other transactions.

Further work (Karagozoglu et al., 2003) shows that splitting of the S&P 500 futures contract resulted in a temporary narrowing of bid-ask spread and average transaction size. However, no significant change in volatility or other lasting measures of liquidity were observed following the split. Chen and Locke (2004), on the other hand, report that the splitting of the S&P 500 futures contract significantly increased the effective bid-ask spread. However, customer trading volume and proprietary trading revenue do not appear to have been affected by the redesign.

Existing studies on algorithmic trading suggest that such trading mechanisms provide liquidity to the financial markets (Hendershott, Jones, & Menkveld, 2011). Much of these research are focused towards the role of High-Frequency Traders (HFT), who are part of the Algorithmic Trader superset. HFTs have assumed the role of the modern market maker (Menkveld, 2013). Algorithmic traders (AT) are seen to help in narrowing spreads, reducing adverse selection and also speeding up price discovery. ATs also improve price efficiency (Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014; Brogaard, Hendershott, & Riordan, 2014).

4 Data Description and Variable Measurement

Our study uses a proprietary dataset obtained from NSE. The dataset includes information on both intra-day order and trade level data for the derivatives segment. The order file records the entire set of order messages received by the exchange throughout the day. The dataset uses flags to identify whether an order was generated from an algorithmic trading terminal or not. It also allows us to identify if the order was placed by a proprietary trader (Prop), a custodian (Cust) or a non-proprietary non-custodian trader(NCNP). Proprietary traders trade on their accounts while the rest trade on behalf of someone else. Financial institutions who are legally barred to have their own account with the exchange, use custodians to trade on their behalf. Non-algorithmic NCNP traders can be assumed to be the closest available proxy for retail traders. On a daily level for each security, we assign the traded volume for a particular trader group as the average of the volume bought and volume sold throughout the day.

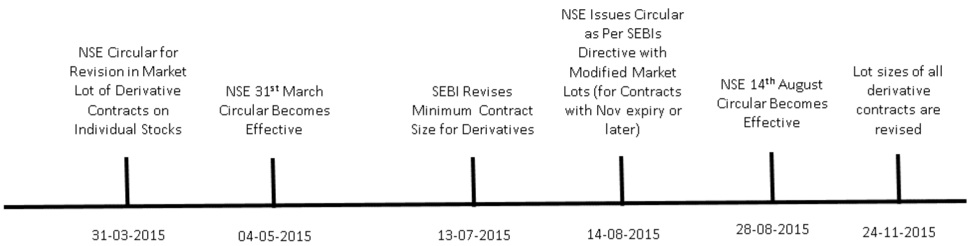
NSE equity market constitutes of 1704 stocks. Out of these stocks, 162 stocks are permitted to be traded in the derivatives segment [8]. Total market capitalization of all stocks traded in the equity segment is INR 99.41 trillion, out of which INR 73.62 trillion, or 74% of the total is contributed by the securities permitted for trading in the derivatives segment [9].

[8] As on 31st December 2015

[9] Market Capitalization data collected from CMIE Prowess database. Data as on 31st

Since 2010, the lot sizes for derivative contracts on individual securities have been standardized, and minimum contract size had been fixed at INR 2 lacs. It was also mandated that the exchanges would review the lot sizes once every six months. Since then, this review of lot sizes has been carried out every year in the months of March and September till March-2015 [10]. As per the circular dated 31st March 2015, the revised lot sizes were applicable from May 4th, 2015. The August 2015 circular that revised the minimum size of the derivative contracts from 2 lacs to 5 lacs was applicable from August 28th, 2015 (only for contracts with November 2015 expiry or later). The events can be summarized using the following timeline Figure 1 which depicts the sequence of various relevant events during 2015.

Figure 1: Timeline of events



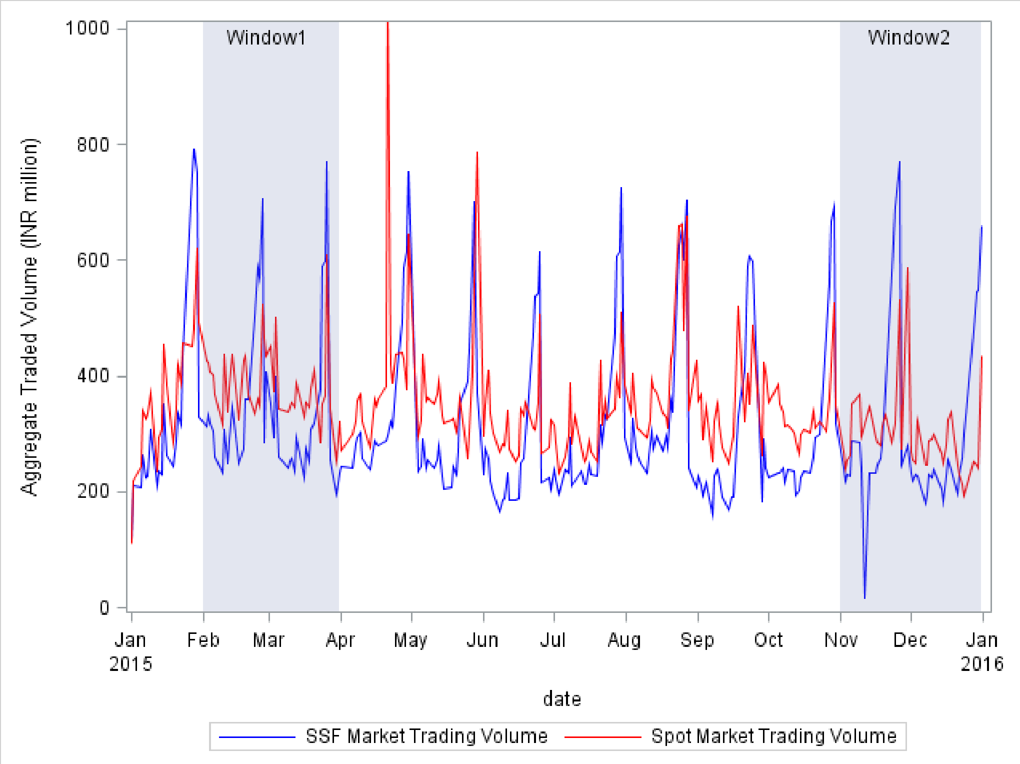
So to examine the impact of the phenomenon of lot size revision on trading behavior, we consider two separate event windows. The pre-window constitutes of the months February and March 2015 and is hereafter referred to as Window 1. As lot size revision for all derivative contracts was applicable from the month of November, we define the post-window, hereafter referred to as Window 2, as the months of November and December 2015. It is further illustrated in following Figure 2. Contrasting our results between only these two windows allows us to focus our attention on the impact caused solely due to the contract size revision. The period in between these two windows contains various other announcements and events that may impact our variables of interest.

As securities are traded at various price levels, and exchanges impose restrictions on the minimum size of the contract, the average traded quantities vary across securities. To standardize the trade sizes across securities, we define a new variable, $Lot\_multiplier_{i,t,contr}$ that is defined as the ratio of the traded quantity for any particular trade i on any date t for a specified

Dec 2015

[10]NSE Circular on 'Revision in Market Lot of Derivative Contracts on Individual Stocks' dated 31st March 2015

Figure 2: Proportion of Algorithmic Trading in 2015 - SSF vs. Spot Market



contract z to the MTU of that contract z on that day. This variable also provides us an idea of the relative size of a trade compared to the minimum requirement. The advantage of using this measure over absolute values of trade is that it gives us the advantage of comparability across securities. We adjust for any changes in the MTU due to corporate actions (i.e., bonus share issue, stock split, etc.).

$$Lot\_multiplier_{i,t,z} = \frac{Trade\_q_{i,t,z}}{MTU_{t,z}} \tag{1}$$

As previously mentioned, MTUs are revised periodically and as such the exchanges do not consider a continuous change in contract value due to any change of prices, barring that due to corporate actions. Therefore it is possible that at any particular time, the minimum contract size for a particular security is significantly different than the stipulated level. To resolve this problem, we propose a similar measure of relative trade size - $Size\_multiplier_{i,t,z}$. We define $Size\_multiplier_{i,t,z}$ as the ratio of the value of each trade to the minimum specified size of the contract.

$$Size\_multiplier_{i,t,z} = \begin{cases} Trade\_val_{i,t,z}/200,000 & \text{before revision} \\ Trade\_val_{i,t,z}/500,000 & \text{after revision} \end{cases} \quad (2)$$

We define the value of each trade i on a date t for a specified contract z as the product of traded quantity and the trade price.

$$Trade\_val_{i,t,z} = Trade\_q_{i,t,z} * Trade\_prc_{i,t,z} \quad (3)$$

It is important to consider that by construction, the *Lot_multiplier* variable cannot take a value less than 1. However, the *Size_multiplier* variable can take values less than 1 in case price of a security drops significantly.

For estimation of intra-day volatility, we use measures of unconditional volatility by Parkinson (1980) and Andersen, Bollerslev, Diebold, and Ebens (2001). Andersen et al. (2001) proposed that realized volatility can be calculated from intra-day return of every five minutes as

$$\sigma^2_{t,Anderson} = \sqrt{\sum_{i=1}^{n_t} (r_{it})^2} \quad (4)$$

where r_{it} is the intra-day return of the i-th five-minute sub-period for the t-th day.

The volatility estimator as proposed by Parkinson (1980) measures the daily volatility based on daily-high and daily-low prices as

$$\sigma^2_{t,Parkinson} = (\frac{(\ln(P_{high,t}) - \ln(P_{low,t}))^2}{4\ln(2)})^{1/2} \quad (5)$$

where $P_{high,t}$ and $P_{low,t}$ are respectively maximum and minimum traded price for the t-th day.

NSE has witnessed significant growth in algorithmic trading activity over the years. As illustrated in figure 3, which plots the algorithmic trading activity in the equity as well as SSF market on a monthly basis, we can see that both these markets have witnessed almost 100% growth in algorithmic trading over the last five years. There does not seem to be any significant difference in algo trading activity between the two markets. Considering that presently algo trades contribute almost 40% of the traded volume, their behavior remains a subject of extreme interest.

Among the various group of traders who use these markets, we can see that percentage contribution of the various trader groups in the spot market and single stock futures market are similar (Table 2). Retail traders, who can be proxied by NCNP non-algo category, contribute almost one-third of the traded volume.

Figure 3: Growth of Algorithmic Trading Over the Years

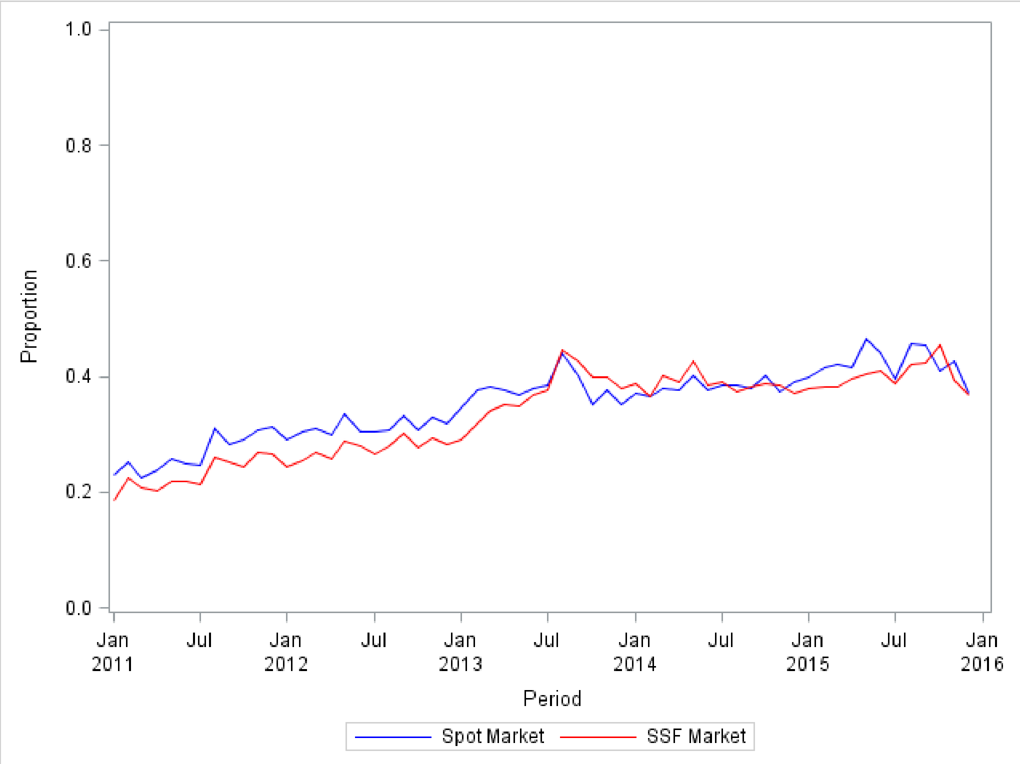


Table 2: Algo - Non Algo Trade proportions for the year 2015

Trader Category	Spot Market	SSF Market
Prop Algo	0.1318	0.1720
Cust Algo	0.2134	0.1198
NCNP Algo	0.0776	0.1076
Prop NonAlgo	0.0745	0.1275
Cust NonAlgo	0.1140	0.1057
NCNP NonAlgo	0.3887	0.3674

5 Analysis

5.1 Algorithmic Trading and Minimum Trading Unit (MTU)

The competitive advantage of algorithmic traders lies in their ability to execute a large number of small trades at very high speed. In the absence of any restrictions on trade sizes, they try to optimize their trade sizes so that it is not large enough so cause significant price impact and also not small enough so that to execute a predefined quantity, they need to carry out too many trades and subsequently incur higher transaction cost. We argue that trade size restrictions as imposed in the case of Indian derivative market, force the trade sizes, especially for the algorithmic traders to the minimum allowable limit or MTU as specified by the exchange.

In a particular trade, the trade size is determined by the smaller of the desired traded quantity of the buyer and the seller. We argue that because of their advantage of speed, algo traders would like to trade in smaller sizes. As such, the trade size ought to be determined by the algo trader. As such, our first testable hypothesis can be articulated as follows.

Hypothesis 1 *In a particular trade if one of the parties (buyer or seller) is algorithmic in nature, the trade size is more likely to be dictated by that trader. In other words, algo traders dictate trade size.*

To test our first hypothesis, we first classify trades based on the type of the parties to the trade. We classify trades into three groups- both parties Non-Algo (Type-0), both parties Algo (Type-1) and one of the parties Algo & the other Non-Algo (Type-2) as illustrated in Table 3. It needs to be considered that we do not differentiate between the Buyer/Seller orientation of the Algo trader, as it should not logically have any impact on trade size. The idea behind this classification is that we expect the trade size for trades where both parties are algo traders (Type-1) to be much smaller than trades where both parties are non-algo traders (Type-0). If our null hypothesis that algo traders dictate trade size is true, we would expect trade sizes for trades where one of the parties is algo trader and the other non-algo trader (Type-2), to be closer to the Type-1 trades compared to the Type-0 trades.

Table 3: Proposed Trade Classification Scheme

Buyer	**Seller**	**Trade Type**
Non-Algo	Non-Algo	Type-0
Algo	Algo	Type-1
Non-Algo	Algo	Type-2
Algo	Non-Algo	Type-2

To compare the trade sizes for these various trade classes, we use relative trade size parameters - Lot-Size Multiplier(LM) and Size Multiplier(SM) as defined earlier. To account for the event of an increase in minimum contract size and subsequent increase in MTU, we compare the results across the two previously defined periods - February & March 2015 (Window 1) and November & December 2015 (Window 2). We calculate the mean of the relative trade size parameters of all trades during the period, without distinguishing between the securities. The mean and standard deviation of the trade size parameters for the two periods (Window 1 and Window 2) can be seen in Tables 4 and 6. As it can be most of the trades take place when one of the parties is an algo trader and the other non-algo trader, or in other words, algo traders are more likely to trade with a non-algo trader compared to a algo trader. We also observe that trade size of the Type-2 trades is much similar to the size of Type-1 trades compared to that of Type-0 trades. We use paired T-Test [11] (Tables 5 and 7) to show that the trade size parameters for Type-1 and Type-2 trades are very similar consistent with our stated hypothesis. Though the difference is statistically significant, the magnitude is very small compared to the difference with Type-0 trades. Trade sizes are largest for Type-0 trades. These behaviors are consistent across Windows 1 and 2.

Table 4: Differences in Relative Trade Sizes (LM & SM) in Window1 (Feb-Mar 2015).

Trade Type	Type Flag	Trade Count	Lot Multiplier		Size Multiplier	
			Mean	Std Dev	Mean	Std Dev
Both Non-Algo (NA)	0	9,793,926	1.7422	4.4228	2.7760	6.6691
Both Algo	1	6,429,504	1.1654	1.1042	1.6345	1.4006
One Algo, Other NA	2	17,625,612	1.2067	1.1507	1.9043	1.8431

Table 5: Paired T-Test to Compare Means

	Lot Multiplier		Size Multiplier	
	Difference	t Stat	Difference	t Stat
Diff (0-1)	0.6899	471.68	1.1415	518.54
Diff (1-2)	-0.1544	-331.3	-0.2698	-382.37
Diff (0-2)	0.5355	371.97	0.8718	400.67

All differences significant at 1% level of significance

As we find that trade size for trades where both the parties are algo traders (Type-1) is very similar to trades where one of the parties is algo trader and the other not (Type-2), it makes logical sense to classify both these trades type of trades as one single class of algo-trade. We propose a modified classification scheme where trades are categorized as algo trades

[11] Satterthwaite's approximate t-test carried out following Moser, Stevens, and Watts (1989). Unequal varainces established through Folded F Test

Table 6: Differences in Relative Trade Sizes (LM & SM) in Window2 (Nov-Dec 2015).

Trade Type	Type Flag	Trade Count	Lot Multiplier		Size Multiplier	
			Mean	Std Dev	Mean	Std Dev
Both Non-Algo (NA)	0	6,100,370	1.5234	3.2283	1.5339	3.1996
Both Algo	1	3,365,595	1.0586	1.2365	1.0433	1.2048
One Algo, Other NA	2	10,359,230	1.1326	0.9930	1.1241	0.9210

Table 7: Paired T-Test to Compare Means

	Lot Multiplier		Size Multiplier	
	Difference	t Stat	Difference	t Stat
Diff (0-1)	0.4648	316.04	0.4907	337.85
Diff (1-2)	-0.0739	-99.73	-0.0809	-112.87
Diff (0-2)	0.3908	291.02	0.4098	308.93

All differences significant at 1% level of significance

if either or both the parties in that particular trade is algorithmic in nature and it is categorized as a non-algo trade if both the parties are non-algorithmic in nature, as illustrated in Figure 8.

Table 8: Proposed Trade Classification Scheme

Buyer	**Seller**	**Trade Type**
Non-Algo	Non-Algo	Type-0 [Non-Algo Trade]
Algo	Algo	Type-1 [Algo Trade]
Non-Algo	Algo	Type-1 [Algo Trade]
Algo	Non-Algo	Type-1 [Algo Trade]

Our next testable hypothesis is a logical extension of our first hypothesis.

Hypothesis 2 *Trade sizes for Algo trades is much smaller than that for Non-Algo trades.*

We compare the trade sizes for the algo and non-algo trades within the two previously defined windows 1 & 2. Consistent with our hypothesis, we find that the lot multiplier and size multiplier values for algo trades are much smaller (Tables 9 and 11) than those for non-algo trades. We use paired T-Test to show that the difference is statistically significant (Tables

10 and 12) in both the periods under consideration. Also, we find that for algo-trades, the value for the size multiplier is close to 1, indicating that algo traders are more likely to execute trades exactly at the MTU. The high standard deviation of Lot multipliers in the case of non-algo trades suggests that non-algo trade sizes are more dispersed compared to algo trades, which are more concentrated around the MTU.

Table 9: Differences in Relative Trade Sizes (LM & SM) between Algo and Non-Algo trades in Window1 (Feb-Mar 2015).

Trade Type	Type Flag	Trade Count	Lot Multiplier		Size Multiplier	
			Mean	Std Dev	Mean	Std Dev
Non-Algo	0	9,793,926	1.7422	4.4228	2.7760	6.6691
Algo	1	24,055,116	1.1654	1.1042	1.8322	1.7400

Table 10: Paired T-Test to Compare Means

	Lot Multiplier		Size Multiplier	
	Difference	t Stat	Difference	t Stat
Diff (0-1)	0.5768	403.03	0.9439	436.91

All differences significant at 1% level of significance

Table 11: Differences in Relative Trade Sizes (LM & SM) between Algo and Non-Algo trades in Window2 (Nov-Dec 2015).

Trade Type	Type Flag	Trade Count	Lot Multiplier		Size Multiplier	
			Mean	Std Dev	Mean	Std Dev
Non-Algo	0	6,100,370	1.5234	3.2283	1.5339	3.1996
Algo	1	13,724,825	1.1144	1.0584	1.1043	0.9987

Table 12: Paired T-Test to Compare Means

	Lot Multiplier		Size Multiplier	
	Difference	t Stat	Difference	t Stat
Diff (0-1)	0.4090	305.67	0.4297	324.72

All differences significant at 1% level of significance

To contrast these results to the scenario in the spot market, we report the average trade sizes for the Nifty 50 stocks for the year 2015 in Table 13. These are the fifty stocks which have the highest market capitalization

Table 13: Comparison of average trade sizes in the spot market for Nifty 50 stocks for the year 2015

	Window-1				Window-2			
	Non-Algo		Algo		Non-Algo		Algo	
NSE Symbol	ATS	ATQ	ATS	ATQ	ATS	ATQ	ATS	ATQ
ACC	44,691	28	30,976	19	38,635	29	27,499	20
ADANIPORTS	29,667	92	19,218	60	21,870	82	18,092	68
AMBUJACEM	22,516	86	16,230	62	31,694	158	17,106	86
ASIANPAINT	38,838	47	24,305	30	36,176	43	22,189	26
AXISBANK	38,272	66	41,417	72	50,376	110	29,286	64
BAJAJ-AUTO	94,844	44	38,037	18	50,402	20	27,929	11
BANKBARODA	18,364	102	23,426	131	22,012	134	27,812	169
BHEL	22,198	85	24,438	93	15,589	88	17,589	99
BOSCHLTD	147,937	6	116,615	4	102,631	5	55,590	3
BPCL	45,145	60	25,281	34	39,670	44	25,516	28
CAIRN	20,800	87	19,282	80	13,945	102	12,805	94
CIPLA	44,558	64	28,553	41	33,623	52	20,642	32
COALINDIA	51,835	141	33,908	91	35,356	108	21,804	66
DRREDDY	72,075	22	38,619	12	52,837	16	49,942	15
GAIL	41,762	104	19,260	48	27,469	79	17,360	51
GRASIM	77,566	21	36,613	10	56,699	15	30,977	8
HCLTECH	108,215	66	30,503	19	45,759	53	19,699	23
HDFC	67,109	51	38,301	29	52,833	44	35,797	30
HDFCBANK	95,495	91	63,069	60	87,359	82	55,319	52
HEROMOTOCO	234,080	88	40,736	15	76,026	29	35,851	14
HINDALCO	20,355	143	20,977	146	18,521	233	24,344	307
HINDUNILVR	40,400	44	27,131	30	41,542	50	22,307	27
ICICIBANK	35,470	107	35,643	107	38,831	148	30,947	118
IDEA	49,549	292	21,721	131	22,289	161	16,777	122
INDUSINDBK	73,328	83	38,358	44	58,020	62	24,094	26
INFRATEL	17,731	48	21,781	59	25,501	64	13,180	33
INFY	87,727	39	50,370	23	47,735	44	35,814	33
ITC	49,879	140	34,090	96	63,717	192	31,033	94
KOTAKBANK	100,699	76	40,205	30	42,230	62	31,785	46
LT	51,721	30	46,691	27	35,451	27	30,522	23
LUPIN	59,207	33	35,412	20	53,249	29	32,789	18
M&M	73,551	61	29,139	24	71,017	55	34,290	27
MARUTI	77,647	21	60,735	17	88,452	19	76,345	17
NTPC	41,839	277	26,130	174	37,959	277	18,273	135
ONGC	33,310	103	22,315	68	30,693	134	17,914	77
PNB	16,828	101	24,883	149	18,691	144	23,118	178
POWERGRID	30,830	205	26,706	178	47,900	356	21,452	159
RELIANCE	41,765	48	36,247	42	40,853	42	36,066	37
SBIN	26,162	90	34,539	119	27,522	116	33,004	139
SUNPHARMA	54,721	56	31,260	32	43,755	58	31,239	41
TATAMOTORS	41,408	73	30,383	54	36,229	91	30,032	75
TATAPOWER	15,200	183	19,821	238	16,007	241	15,108	228
TATASTEEL	21,108	60	26,764	77	21,656	90	30,681	128
TCS	72,700	28	41,244	16	94,367	39	40,409	17
TECHM	85,433	58	42,634	26	30,237	57	22,170	42
ULTRACEMCO	83,999	28	27,012	9	96,549	34	24,465	9
WIPRO	44,842	69	24,656	38	47,478	84	20,638	37
YESBANK	39,465	48	34,323	42	37,828	52	27,520	37
ZEEL	38,557	110	19,550	56	38,955	95	15,852	39

ATS refers to Average Trade Size of any trade in INR
ATQ refers to Average Trade Quantity of any trade

as on 31st Dec 2015. All of these stocks are also traded in the derivatives market.

Similar to the SSF market, it can be seen that average trade sizes for the algo trades are much smaller than that of the non-algo trades. In the absence of minimum trading unit restriction, the trade quantities are not de-facto set to the minimum units allowable (one unit in case of the spot market). Instead, traders optimize trade quantities to price impact and transaction costs. The average trade sizes (in INR terms) as well the trade quantities differ significantly across stocks. The average trade sizes are also significantly smaller than the minimum size specified in the derivatives market. Also, the trade sizes do not seem to have been impacted by the phenomenon of contract size revision.

5.2 How Do Algorithmic Traders React To Change in MTU?

As seen in the earlier section, algo-traders prefer to trade in small sizes, preferably as close as possible to the MTU. As a result of SEBI's revision of minimum contract sizes, the MTU for the various securities were also revised upward. This lead to increase in the value of individual trades and subsequently higher margin requirements. Algo traders have their incentive to continue to trade exactly at or close to the MTU. But for the non-algo traders, it is difficult to sustain higher relative trade sizes as previous to contract size revision. As such we expect that difference in lot multipliers between algo and non-algo trades to come down due to this revision.

Hypothesis 3 *Upward revision in minimum contract size leads to a reduction in the difference of relative trade sizes between algorithmic and non-algorithmic trades.*

We try to estimate the impact of contract size revision through the following regression equation. Trade Dummy is 1 for algo trades and 0 for non algo trades. We expect the difference in lot multiplier and size multiplier between algo and non-algo trades to come down after the contract revision. Similar to the previous case, we only consider data points in window 1 and window 2. The *Revision_Dummy* is 1 for window 2 and 0 for window 1. We expect the coefficient of the $Trade\_Dummy$ to be negative as Algo trades sizes are supposed to be smaller than non-algo trade sizes. The *Revision_Dummy* is also expected to have a negative sign as the denominators in the multiplier definitions increase post the revision. The revision is supposed to impact multiplier values for the non-algo trades more than the algo trades, for whom the multiplier values will anyways be close to one. As such we expect the interaction term to be positive.

$$Lot\_Multiplier_i = \beta 1 * TradeDummy_i + \beta 2 * RevisionDummy + \beta 3 * (TradeDummy_i * RevisionDummy) \quad (6)$$

$$Size\_Multiplier_i = \beta 1 * TradeDummy_i + \beta 2 * RevisionDummy + \beta 3 * (TradeDummy_i * RevisionDummy) \quad (7)$$

Consistent with our hypothesis we find that the interaction term comes out to be positive (Table 14 and Table 15), suggesting that the difference in lot-multiplier or trade size-multiplier between algo and non-algo trades

Table 14: Difference in Difference Regression Model to Estimate the Impact of Contract Size Revision on Algo-Trade Sizes

Dependent Variable: Lot multiplier

Variable	Parameter Estimate	Standard Error	t Value	$Pr > \|t\|$
Intercept	1.74217	0.00076	2306.71	$< .0001$
Trade Dummy	-0.57675	0.00090	-643.76	$< .0001$
Revision Dummy	-0.21878	0.00122	-179.46	$< .0001$
(Trade Dummy)* (Revision Dummy)	0.16779	0.00146	115.09	$< .0001$
Number of Obs	53,674,237			
Adj R-Sq	0.0103			

Table 15: Difference in Difference Regression Model to Estimate the Impact of Contract Size Revision on Algo-Trade Sizes

Dependent Variable: Size multiplier

Variable	Parameter Estimate	Standard Error	t Value	$Pr > \|t\|$
Intercept	2.77603	0.00105	2632.49	$< .0001$
Trade Dummy	-0.94387	0.00125	-754.55	$< .0001$
Revision Dummy	-1.24209	0.0017	-729.71	$< .0001$
(Trade Dummy)* (Revision Dummy)	0.51421	0.00204	252.61	$< .0001$
Number of Obs	53,674,237			
Adj R-Sq	0.0273			

reduces post the contract size revision. The trade dummy coefficient is negative suggesting that trade sizes are smaller for algorithmic trades.

Next, we inspect further into the trading behavior of individual trading groups. In our dataset, we can identify traders as Propitiatory (Traders trading on their own account) or Clients. Clients are further classified into Custodians [12] or Non-Prop Non-Custodians (NCNP). For our analysis, the non-algorithmic NCNP traders can be considered as the closest available proxy to retail traders.

As the value of individual trades increases because of the contract size revision, we expect the number of trades to go down. Considering that Custodian traders are primarily institutional investors and institutional traders are known to trade on information. Existing literature (Easley &

[12] NSE provides a service to entities like FIIs, Mutual Funds, NRIs, Domestic Body Corporates & Domestic Financial Institutions etc. to execute trades through Custodians

O'Hara, 1987) suggests that the trade sizes for the Custodian traders are supposed to be higher than others. But using higher trade sizes makes them easily identifiable. As such it may be expected that non-algo Custodian trade sizes would be higher and algo Custodian trade sizes would be much smaller.

Table 16: Trader Group Wise Behaviour [Window 1: Feb & Mar 2015]

Trader Group	Trade Count	Avg Lot Multiplier	SD Lot Multiplier	Avg Size Multiplier	SD Size Multiplier
Algo Cust	4,096,744	1.25	1.66	1.94	2.53
Algo Prop	7,118,949	1.09	0.68	1.70	1.12
Algo NCNP	4,026,618	1.13	0.86	1.79	1.37
NonAlgo Cust	1,768,314	2.81	8.15	4.31	12.38
NonAlgo Prop	3,920,683	1.45	2.47	2.28	3.69
NonAlgo NCNP	12,917,736	1.32	2.15	2.12	3.26

Table 17: Trader Group Wise Behaviour [Window 2: Nov & Dec 2015]

Trader Group	Trade Count	Avg Lot Multiplier	SD Lot Multiplier	Avg Size Multiplier	SD Size Multiplier
Algo Cust	2,975,991	1.16	1.65	1.14	1.57
Algo Prop	3,514,480	1.07	0.57	1.06	0.50
Algo NCNP	2,054,739	1.07	0.72	1.07	0.70
NonAlgo Cust	1,103,409	2.53	6.39	2.50	6.30
NonAlgo Prop	2,493,373	1.28	1.60	1.28	1.54
NonAlgo NCNP	7,683,203	1.20	1.44	1.20	1.44

As reported in Table 16 and Table 17 we find that Prop Algo (Superset of High-Frequency Traders) and Retail traders remain most active traders in the Single stock futures segment. As expected we find that trade counts go down following the revision. Lot multipliers and size multipliers for algo traders remain lower than non-algo traders. For algo traders the value of the $Lot\_Multiplier$ and the $Size\_Multiplier$ remain close to 1. The multiplier values for the Custodian traders is largest for both algorithmic as well as non-algorithmic group, but the values are significantly lower in the case of the algo group. As such it may be concluded that institutional investors use algorithms to split up their trades to remain less identifiable. As expected, Prop Algo traders, who are the superset of HFT traders trade in smallest trade sizes among these groups.

5.3 Impact of Contract Size Revision on Overall Traded Volume

The SEBI circular regarding the modification of contract size for derivative segments was issued on 13th July 2015[13]. Following the circular, NSE issued another circular on 7th August 2015 specifying the revised market lots of the derivative securities. For all the securities, the revision was effective for securities expiring on November 2015 and later. NSE futures contracts generally expire on the last Thursday of the expiry month. In the case where the last Thursday is a trading holiday, the contracts expire on the previous trading day.

Table 18: Details of the NSE Contract size revision schedule. The contract size was revised for November 2015 expiries and later. NM, MM and FM stand for Near Month, Middle Month and Far Month contracts respectively

Contract Expiry Date	**NM**	**MM**	**FM**
30/07/2015			
27/08/2015			
24/09/2015			Revised
29/10/2015		Revised	Revised
26/11/2015	Revised	Revised	Revised
31/12/2015	Revised	Revised	Revised

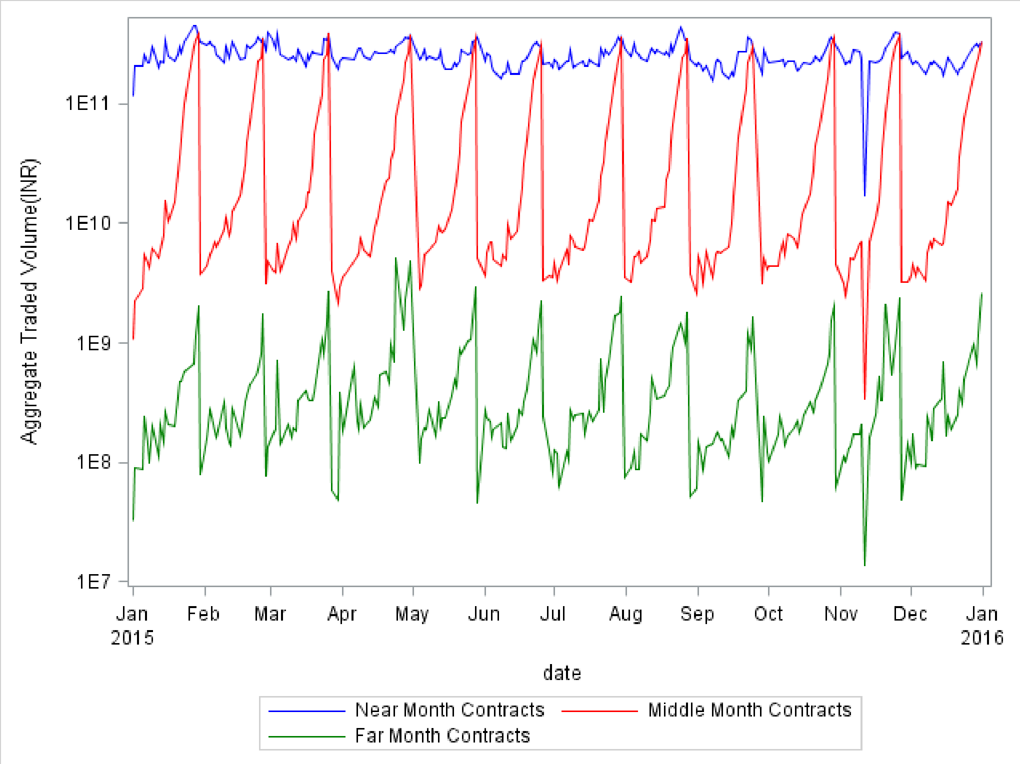
In the existing literature, Karagozoglu and Martell (1999) inspect the impact of lot size revision in index futures using an event study model controlling for intra-day volatility and futures price level.

$$\begin{aligned} Lot\_Multiplier_i = \beta 1 * TradeDummy_i + \beta 2 * RevisionDummy + \\ \beta 3 * (TradeDummy_i * RevisionDummy) \end{aligned} \tag{8}$$

For our panel data estimation, we consider our period of interest from 13th June 2015 (1 month prior to SEBI's announcement of minimum contract size revision) to 31st December 2015. *Announcement Dummy* takes up the value 1 if the date is within the period of 14th July 2015 to 13th August 2015 (within one month of SEBI's announcement regarding contract size revision), else it takes up the value 0. *FUTSTK Daily Return* is the logarithmic return of SSF prices. To control for the various other parameters which may affect traded volume specifically in the SSF market, we refer to Białkowski and Jakubowski (2012). To control for the high correlation in traded volume between spot market and futures market, we use spot market traded volume as a control variable. Following Table 18

[13]SEBI Circular No. CIR/MRD/DP/14/2015 dated 13th July 2015

Figure 4: Daily Traded Volume (INR) in NSE Single Stock Futures Market segregated according to contract expiries



Event Dummy takes up the value of 1 if the size of the specified contract was revised, 0 otherwise.

$$Fut\_Volume_{i,j,} = \beta 1 * TradeDummy_i + \beta 2 * RevisionDummy + \beta 3 * (TradeDummy_i * RevisionDummy) \quad (9)$$

The results obtained from panel data regression models are documented in Table 19. To study the impact of SEBI's announcement and subsequent actual implementation, we run two separate models (Model 1 and Model 2). As seen from the results, the announcements seem to reduce traded volume (INR) significantly, and the actual implementation seems to have a positive impact. To capture the effect of the announcement, we have considered a +1/-1 month window around the announcement date of 13th July 2015. In model 2, we consider our period from 14th August 2015 to 31st December 2015. The significant negative value of the announcement dummy represents a psychological impact rather than an economic interpretation. The positive value of the *Event Dummy* is possibly counter-intuitive, but we argue that rather than an actual positive impact it is more

Table 19: Panel Data Analysis of SEBI's announcement and subsequent implementation of contract size revision on Single Stock Futures traded volume (INR)

Dependent Variable: ln(Fut Traded Volume)

	(1)	(2)	(3)	(5)	(6)
Announcement Dummy	-0.292***		-0.226***	-0.226***	-0.228***
	(-9.94)		(-8.78)	(-8.78)	(-8.87)
Event Dummy		0.135***	0.0651***	0.0651***	0.0757***
		(8.96)	(3.51)	(3.51)	(4.16)
Days to Expiry	-0.0826**	-0.0886***	-0.0873***	-0.0873***	-0.0856***
	(-19.14)	(-23.89)	(-21.81)	(-21.81)	(-21.78)
Fut Daily Return	-0.572*	-0.654***	-0.652***	-0.732***	-0.524**
	(-2.49)	(-3.62)	(-4.15)	(-4.28)	(-3.16)
ln(Spot Mkt Volume)	0.794***	0.669***	0.711***	0.711***	0.707***
	(34.33)	(44.24)	(53.62)	(52.89)	(44.79)
$\sigma_{Fut,Anderson}$				-1.474**	
				(-2.83)	
$\sigma_{Spot,Anderson}$				1.407	
				(1.26)	
$\sigma_{Fut,Parkinson}$					337.1***
					(7.63)
$\sigma_{Spot,Parkinson}$					-265.2***
					(-8.61)
Constant	5.653***	8.255***	7.445***	7.437***	7.463***
	(11.23)	(24.55)	(24.48)	(24.22)	(21.82)
N	16854	34748	51602	51602	51602
Adj R Square	0.39	0.448	0.424	0.424	0.434

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

of a correction mechanism following the negative impact of the announcement. The standard errors have been adjusted for possible autocorrelation and heteroskedasticity.

It can be certainly argued that traded volume in Futures market is serially correlated. Present open trade positions certainly influence future trading patterns. As a robustness check, we also consider the lagged traded volume as a control variable and re-run the model. The result of the dynamic panel data analysis is reported in Table 20. As seen from the results, the signs of the *Announcement Dummy* or the *Event Dummy* does not change upon the modification. Also, the results are robust on the number of lagged dependent variable considered in the model.

To demonstrate that the announcement effect is psychological and tran-

Table 20: Dynamic Panel Data Analysis of SEBI's announcement and subsequent implementation of contract size revision on Single Stock Futures traded volume (INR)

Dependent Variable: ln(Fut Traded Volume)

	(1)	(2)	(3)
L.ln(Fut Traded Volume)	0.0342***	-0.0728***	-0.354***
	(3.32)	(-4.80)	(-12.68)
L2.ln(Fut Traded Volume)		-0.0942***	-0.239***
		(-8.36)	(-10.85)
L3.ln(Fut Traded Volume)			-0.144***
			(-7.17)
Announcement Dummy	-0.633***	-0.575***	-0.526***
	(-11.97)	(-10.72)	(-9.16)
Event Dummy	2.392***	2.453***	2.496***
	(19.44)	(19.74)	(19.84)
Days to Expiry	-0.100***	-0.0986***	-0.0949***
	(-21.88)	(-21.64)	(-20.64)
Fut Daily Return	-0.347*	-0.380*	-0.760
	(-2.45)	(-2.56)	(-1.83)
ln(Spot Mkt Volume)	0.650***	0.632***	0.574***
	(49.10)	(39.23)	(20.30)
Constant	7.771***	11.90***	23.74***
	(22.75)	(23.43)	(18.88)
N	25957	15913	6933

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

sient in nature, we do a week by week analysis of traded volume. The results are reported in Table 21. Model 1 is same as in the earlier analysis where we consider a +1/-1 month window around the announcement date of 13th July 2015. In model 2, we introduce the effect of a *Week1* dummy variable which takes up the value 1 if the date is within the period of 14th July to 17th July 2015, i.e., immediate week after the revision. Similarly, in model 3 and 4, we introduce dummy variables for the following two weeks. Consistent with our hypothesis we find that magnitude of the interaction effect between the *Announcement Dummy* and week dummies is strongest in the immediate week and reduces as we move further away from the announcement date.

To explain why the minimum contract size revision did not reduce traded volume in the single stock futures market, we look at the average trade sizes over the year 2015 as depicted in Figure 5. As the revision was

Table 21: Week by week impact of the SEBI's announcement of contract size revision

Dependent Variable: ln(Fut val)

	(1) Overall	(2) Week 1	(3) Week 2	(4) Week 3
Constant	5.6529***	6.0828***	5.85762***	6.2010***
	(0.5032)	(0.5116)	(0.5077)	(0.5034)
Announcement Dummy	-0.2925***	-0.2335***	-0.2673***	-0.4028***
	(0.0294)	(0.0286)	(0.0295)	(0.0312)
Announcement*Week1		-0.2596***		
		(0.0235)		
Announcement*Week2			-0.1431***	
			(0.0214)	
Announcement*Week3				0.5257***
				(0.0218)
Days to Expiry	-0.0826***	-0.0819***	-0.0838***	-0.0777***
	(0 .0043)	(0.0043)	(0 .0043)	(0 .0042)
SSF Daily Return	-0.5725*	-0.2803	-0.6204***	-0.6698***
	(0.2298)	(0.2240)	(0.2306)	(0.2317)
ln(Cash Traded Volume)	0.7944***	0.7715***	0.7865***	0.7573***
	(0.0231)	(0.0234)	(0.0233)	(0.0231)
N	16854	16854	16854	16854

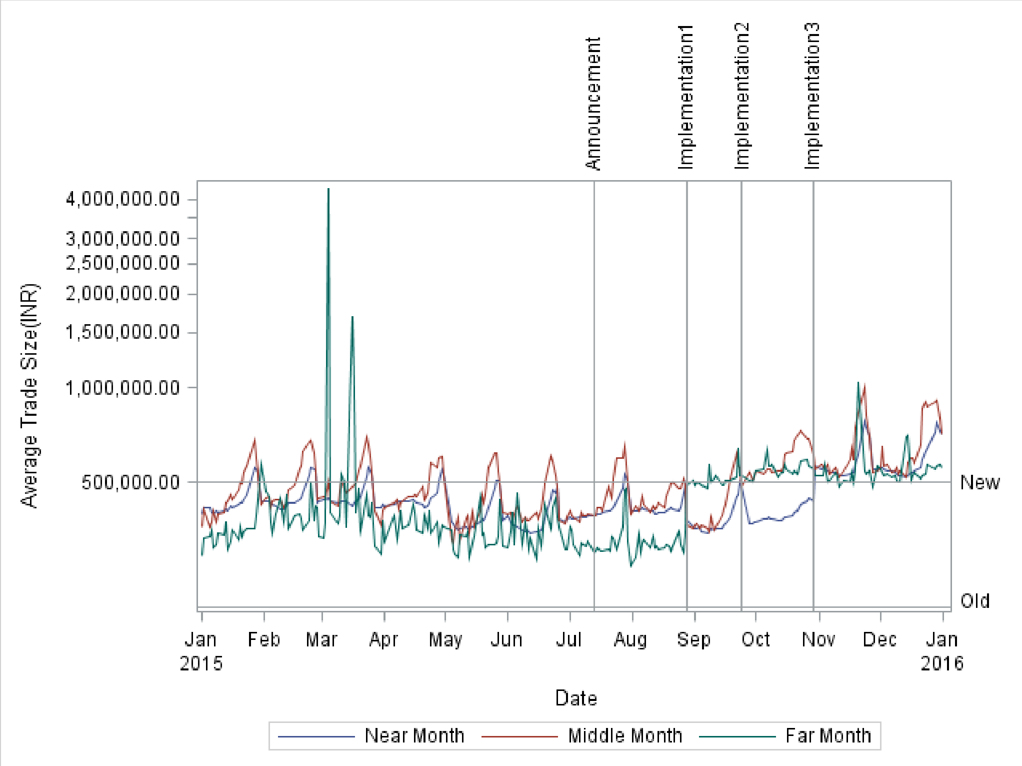
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effective from a particular expiry(November 2015) rather than a particular date, the actual implementation took place on three different dates for three different types of contract, namely Near Month(NM), Middle Month(MM) and Far Month(FM). As seen from the plot, the average trade sizes for all contract types were much larger than the minimum stipulated level of INR 2 lacs. After the revision, we find that the average trade sizes are much closer to the level of minimum contract size. So rather than a complete overhaul to force out certain market participants, it seems that SEBI's revision notification was just a modification to adhere to current standards.

6 Conclusion

This paper has important implications for the academicians and regulatory authorities alike. We investigate how minimum contract size restrictions impact the trading behavior of various market participants, in particular, that of algorithmic traders. We find that in a market situation with significant participation of algorithmic traders, minimum trading unit restrictions

Figure 5: Average Trade Size (INR) in NSE Single Stock Futures Market. Announcement refers to the date of SEBI's announcement - 13th July 2015. Implementation1, Implementation2, and Implementation3 refer to the three dates on which the revision was effective for Far Month, Middle Month and Near Month contracts. Old contract size refers to the value of INR 2 lacs, and new contract size refers to INR 5 lacs.



effectively forces trade sizes to the MTU. Also, this phenomenon is true for almost two-thirds of the total trades in the derivatives market, where at least one of the parties is an algo trader.

Consistent with the notion that institutional investors are informed and informed traders trade in larger trade sizes, we find that trade sizes for non algorithmic institutional traders are significantly larger. While using algorithms, however, they are able to significantly reduce the trade sizes, which prevents them from being easily identifiable.

To observe how these trading behaviors are impacted by regulatory changes, we utilize the natural laboratory setup provided by the market regulator SEBI's revision of minimum contract size for derivative securities. We find that the event did not affect the typical trading behavior of various trader groups. Algo traders continue to trade close to the minimum contract size, while Non-algo traders, who typically trade at relatively larger sizes are forced to trade closer to the minimum contract size post the revision. We find that though the actual implementation of contract size re-specification did not significantly affect overall traded volume, the announcement acted as a significant negative shock, from which the market subsequently recovered.

References

Ahn, H.-J. (2014). Does Trading by Small Investors Improve or Deteriorate Price Efficiency? Evidence from the Minimum Trade Unit Changes on the Korea Exchange. *International Journal of Financial Studies*, *2*(2), 203–219. Retrieved from `http://www.mdpi.com/2227-7072/2/2/203/` doi: 10.3390/ijfs2020203

Amihud, Y., Mendelson, H., & Uno, J. U. N. (1999). Number of Shareholders and Stock Prices: Evidence from Japan. *The Journal of Finance*, *54*(3), 1169–1184. doi: 10.1111/0022-1082.00141

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, *61*(1), 43–76. doi: 10.1016/S0304-405X(01)00055-1

Angel, J. J., Harris, L. E., & Spatt, C. S. (2011). Equity Trading in the 21 st Century. *Quarterly Journal of Finance*, *01*(01), 1–53. Retrieved from `http://www.worldscientific.com/doi/abs/10.1142/S2010139211000067` doi: 10.1142/S2010139211000067

Bertsimas, D., & Lo, A. W. (1998). Optimal control of execution costs. *Journal of Financial Markets*, *1*(50), 1–50. doi: 10.1109/5992.805135

Białkowski, J., & Jakubowski, J. (2012). Determinants of Trading Activity on Single Stock Futures Market-Evidences from Eurex Exchange. *The Journal of Derivatives*, *19*(3), 29–47. doi: 10.3905/jod.2012.19.3.029

Bjursell, J., Frino, A., Tse, Y., & Wang, G. H. K. (2010). Volatility and trading activity following changes in the size of futures contracts. *Journal of Empirical Finance*, *17*(5), 967–980. Retrieved from `http://dx.doi.org/10.1016/j.jempfin.2010.08.003` doi: 10.1016/j.jempfin.2010.08.003

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency Trading and Price Discovery. *Review of Financial Studies*, *27*(8), 2267–2306. doi: 10.1093/rfs/hhu032

Chaboud, A. P., 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. doi: 10.1111/jofi.12186

Chen, J., & Locke, P. R. (2004). Splitting the S&P 500 futures. In *Journal of futures markets* (Vol. 24, pp. 1147–1163). doi: 10.1002/fut.20133

Easley, D., & O'Hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, *19*, 69–90.

Gozluklu, A. E., Perotti, P., Rindi, B., & Fredella, R. (2015). Lot Size Constraints and Market Quality: Evidence from the Borsa Italiana. *Financial Management*, *44*(4), 905–945. doi: 10.1111/fima.12105

Hauser, S., & Lauterbach, B. (2003a). The Impact of Minimum Units on Stock Trading Value and Price Volatility. *Journal of Financial and Quantitative Analysis*, *38*(3), 575–589.

Hauser, S., & Lauterbach, B. (2003b). The Impact of Minimum Units on Stock Trading Value and Price Volatility. *Journal of Financial and Quantitative Analysis*, *38*(3), 575–589.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does Algorithmic Trading Improve Liquidity? *The Journal of Finance*, *LXVI*(1), 1–34. doi: 10.1111/j.1540-6261.2010.01624.x

Huang, R. D., & Stoll, H. R. (1998). Is it time to split the S&P 500 futures contract? *Financial Analysts Journal*, *54*(1), 23–35. doi: http://dx.doi.org/10.2469/faj.v54.n1.2142

Isaka, N. (2014, mar). Long-run effects of minimum trading unit reductions on stock prices. *International Review of Finance*, *14*(1), 75–103. Retrieved from `http://doi.wiley.com/10.1111/irfi.12026` doi: 10.1111/irfi.12026

Karagozoglu, A. K., & Martell, T. F. (1999). Changing the Size of a Futures Contract: Liquidity and Microstructure Effects. *The Financial Review*, *34*(4), 75–94. doi: 10.1111/j.1540-6288.1999.tb00470.x

Karagozoglu, A. K., Martell, T. F., & Wang, G. H. K. (2003). The split of the S&P 500 futures contract: Effects on liquidity and market dynamics. *Review of Quantitative Finance and Accounting*, *21*(4), 323–348. doi: 10.1023/B:REQU.0000004782.92370.89

Kumar, U., & Tse, Y. (2009). Single-stock futures: Evidence from the Indian securities market. *Global Finance Journal*, *20*(3), 220–234. Retrieved from `http://dx.doi.org/10.1016/j.gfj.2009.06.004` doi: 10.1016/j.gfj.2009.06.004

Menkveld, A. J. (2013, nov). High frequency trading and the new market makers. *Journal of Financial Markets*, *16*(4), 712–740. Retrieved from `http://www.sciencedirect.com/science/article/pii/S1386418113000281` doi: 10.1016/j.finmar.2013.06.006

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*(3), 483–510.

Moser, B. K., Stevens, G. R., & Watts, C. L. (1989). The two-sample t test versus satterthwaite's approximate f test. *Commu-*

nications in Statistics - Theory and Methods, *18*(11), 3963–3975. Retrieved from http://dx.doi.org/10.1080/03610928908830135 doi: 10.1080/03610928908830135

O'Hara, M., Yao, C., & Ye, M. (2014). What's not there: Odd lots and market data. *Journal of Finance*, *69*(5), 2199–2236. doi: 10.1111/jofi.12185

Parkinson, M. (1980). The Extreme Value Method for Estimating the Variance of the Rate of Return. *The Journal of Business*, *53*(1), 61. doi: 10.1086/296071