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Algorithmic Trading: The Intelligent Trading Systems and Its Impact on Trade Size

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ABSTRACT

Financial markets have come across a phenomenal adoption of advanced and complex technologies in the pursuit of efficient markets. Algorithmic Trading (AT) is one of the prominent moves in this direction and is widely adopted across world markets. The existing literature on AT and its impact on markets is still in the nascent stage primarily due to the inability of most of the markets to directly identify AT. In this study, we directly identify AT and examine its impact on trade sizes which has a key impact on liquidity and price impact of trades. We also use the inverse of Order-to-Trade (1/OTR) ratio as a measure of algorithmic trading efficiency and examine its relationship with size. It is expected that AT has the capability to break large orders into smaller sizes in order to access liquidity and reduce price impact. In this study, we provide empirical evidence for the size effects of AT with direct identification of AT.

1. Introduction

Algorithmic Trading (AT) is a prominent phenomenon in our electronic trading markets across the globe. Developed markets accepted AT in order to take the advantage of latency and improve upon the profitability of market participants. However, developing markets struggling with liquidity issues accepted AT in order to tackle the issues pertaining to liquidity supply and making their markets more efficient. Though every market had their own reasons to adopt AT but did AT actually fulfill those expected motives, has not been examined extensively in existing literature. The prime reason for the lack of extensive research on AT is due to the limitation of researchers to directly identify AT. Not many exchanges define and identify AT, however we have an advantage of the unique setting where Securities Exchange Board of India (SEBI) has mandated the tagging of all AT orders and trades with unique identifiers in order to create an audit trail. This was purposefully done to ensure that the reasons for flash crashes and other erroneous trades could be easily identified. In this study we use direct identification of AT for our analysis unlike many of existing literature which uses proxy for AT measurement.

1.1. *Why algorithmic trading and trade size should be related?*

Algorithmic trading has the capability to quickly gather the information from the market and also incorporate the same in the market thereby facilitating an efficient trade. One aspect of AT that we have always come across is that it places the orders at a very high frequency and also modifies its orders rapidly. This leads to one of the major apprehensions pertaining to high frequency order placement: what happens if the orders are placed just to drive the prices in a specific direction. Existing literature and the practitioners have always supported AT in this aspect by suggesting that AT is smart enough to place the orders in small quantity of stocks to reduce the price impact as AT is not only going to place the orders it's also going to trade. So, any price impact will actually affect the cost of trading for the AT. Even though if someone wants to trade huge chunk of stocks, what AT does is, it places smaller orders over a period of time to fulfill the eventual goal of trading the bulk. This reduces the cost of the trading for the traders.

1.2. *Algorithmic trading efficiency: a novel approach*

Taking a cue from the existing literature, in this study we try to establish if AT has any impact on trade sizes. We expect the trade sizes to

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decline with rise in algorithmic trading intensity and also with rise in algorithmic trading efficiency. Algorithmic trading efficiency is another aspect of AT which has not been studied in existing literature (Dubey et al., 2021). We are one of the first few to examine the inverse of Order-to-Trade Ratio (OTR) as a measurement of algorithmic trading efficiency and suggest that the efficiency of AT should reflect not only on how fast they submit the orders but also on how many of such orders actually result in actual trades.

The rest of the paper is organized as: Section 2 discusses literature on AT and trade size. Section 3 describes the data, variables and methodology used in this study. Section 4 illustrates the hypothesis development, results, interpretations and discussion and; Section 5 provides concluding remarks on size effects of AT.

2. Literature review

The existing literature on AT is limited primarily due to lack of direct identification of AT. The literature on AT's impact on order/trade sizes is even more scarce but it has been often assumed by most of the researchers that AT has the capability of breaking large orders into smaller sizes in order to reduce the price impacts. We discuss below the limited literature on AT's impact on trading/order sizes.

2.1. Algorithmic trading and trade sizes

Hendershott and Riordan (2013) examine the relationship of Algorithmic Trading (AT) with market liquidity in the 30 Deutscher Aktien Index (German Stock Index, DAX) stocks on the Deutsche Boerse (DB). Trade size is among one of the various liquidity measures (quoted spread, effective spread, depth, trade size) studied by them. They use smaller trade sizes as a proxy for liquidity. They use categorical and frequency representation to substantiate their theoretical understanding and their findings. Their trade participant's categorization with respect to the various volume weighted, size weighted, order weighted and transaction weighted trades led to the conclusion about the dominance of AT in smaller size categories. Their report that the proportion of AT exceeds 68% and 57% in the 2 smallest trade-size categories (0–499 & 500–999 shares). They argue that this also suggests that AT uses small trades which in-turn limits their price impact.

Hendershott et al. (2011) examine the impact of AT on liquidity. They examine the impact of AT on some of the non-spread measures like trade size. In their study, they find AT is significantly responsible for lower trade sizes in the largest quintiles. They confirm that the increase in AT is one of the reasons for observing smaller average trade sizes. They even regress AT on liquidity variables based on trade size categories and find that liquidity seem to be significantly improving in quintiles with smaller trade size categories.

2.2. Algorithmic trading efficiency

Dubey et al. (2021) are the first to explore inverse of Order-to-Trade Ratio (OTR) as a measure of algorithmic trading efficiency and they argue that if AT is efficient then "*its orders should lead to a greater number of trades thereby creating liquidity and also making the prices informationally efficient*". Authors in this study observe the simultaneous improvement in market quality along with algorithmic trading efficiency. However, they fail to examine how OTR impacts the order/trade sizes and thereby the impact of trade sizes on liquidity, volatility and price discovery.

2.3. Algorithmic trading and market efficiency

Hendershott et al. (2011), Hendershott and Riordan (2013), Brogaard et al. (2014), Nawn and Banerjee (2019a) and Nawn and Banerjee (2019b) suggest that AT does improve the liquidity, volatility and price discovery and thereby creating an environment inching towards efficient markets. On the other hand, Arévalo et al. (2017), Martins and Neves (2020), Naranjo and Santos (2016), Tsinaslanidis and Zapranis (2016) highlight the pattern recognition and the role of charting and technical analysis towards forecasting stock prices and they indicate the technical aspects of automated trading. Fuzzy Candlestick patterns, flag pattern recognition, genetic algorithms are at core of the literature towards identifying patterns and thereby defying the market efficiency. The conflicting approach towards the market and the trades in market highlights the two schools of thoughts but all the participants including the regulators do strive for an efficient market with improved liquidity, reduced volatility and a speedy price discovery.

2.4. Algorithmic trading identification

The evidences from the existing literature are consistent with the idea that, AT has the ability to break or split larger orders into smaller ones so as to avail or provide liquidity and also making these trades happen without much impact on the price. Therefore, AT is expected to produce smaller order and trade sizes. These studies have only one limitation that, they use proxy measures of AT such as message traffic or synonymously use high frequency trading (HFT) with AT. Authors (Dubey et al., 2017, 2021; Hendershott & Riordan, 2013) do acknowledge that reliability of the findings would be better if AT can be identified directly. In this study we overcome these limitations as we have a unique setting where we have direct identification of AT as provided by the National Stock Exchange of India (NSE) due to the regulatory mandate by SEBI, the market regulator.

3. Data and variable construction

We examine Nifty 50 stocks listed on the National Stock Exchange of India (NSE) for our study. We use Nifty 50 stocks as they are most actively traded and are a representative sample for the various industries and sectors of the economy. The data pertaining to algorithmic trading is obtained from NSE DOTEX from their Order Level Historical Dataset for Sep 2012 to Aug 2013 (12 Months, 248 trading days). We clean the dataset by omitting the stocks which has inconsistent (missing observation and data) data even on a single trading day during the data sample. Finally, we arrive at a dataset of 49 NSE Nifty Stocks.

3.1. The rationale for data

The NSE DOTEX dataset contains standard details of tick-by-tick order level data, trade level data pertaining to Cash/Capital Market segment for all stocks listed on exchange (NSE). The dataset comes with a unique identification flag for AT (0 for Algo, 1 for Non-Algo). The dataset captures high frequency trade and order level information up to the 65536th fraction of a second. The order level data contains information on 17 different variables and the trade level data provides information on 14 different variables. Our dataset counters the criticism of a small sample of data as was the case in Groth, 2011 (5 days) and Brogaard et al. 2014 (5 days), Aggarwal & Thomas, 2014 (59 days), Dubey et al., 2017 (40 days). The above authors also suggest use of longer period of data for reliable results and most importantly a direct identification of AT. As suggested by the authors, we benefit from SEBI's circular dated 30th March 2012 that brings the policy that "all algorithmic orders are tagged with a unique identifier provided by the stock exchange in order to establish audit trail". This circular not only brings the clear identification of algorithmic trading, but also brings a holistic definition of AT for the first time. Hence, our data set for the period 1st September 2012 to 31st August 2013 captures the unambiguous and continuous data on AT. Given the clear flag for AT, the concerns regarding the reliability and validity of proxy (as a measure of AT) and quantification of its impact on order/trade sizes is eliminated. We collect other firm level information from CMIE Prowess database (E.g.: market capitalization, share turnover, market to book ratio and price of the stocks).

Table 1
Summary Statistics (Liquidity, Volatility and Price Discovery Measures, Quintile Wise). This table presents summary statistics for the 49 constituents of the NSE Nifty 50 index between March 1, 2013 and August 31, 2013. The dataset contains order level data from National Stock Exchange provided by NSE DOTEX along with market capitalization, share turnover, market to book ratio and adjusted closing prices data obtained from CMIE Prowess database. The dataset is sorted into quintiles based on market capitalization, where quintile 5 contains largest-cap stocks. All the variables are 99% winsorized.

Variable	Description	Source	Mean	Mean Q1	Mean Q2	Mean Q3	Mean Q4	Mean Q5	Symbol
$Size_{it}$	Traded Quantity	DOTEX	65.92	69	107	43	60	51	TradeSize
$AT\_Intensity_{it}$	Algorithmic trading intensity	DOTEX	69.74	64.33	63.13	78.10	72.38	74.13	AT_Intensity
OTR_{it}	Order-to-trade Ratio	DOTEX	22.92	21.64	18.96	23.14	24.94	24.87	OTR
$MBRatio_{it}$	Log of Market to book ratio (daily)	Prowess	0.97	0.52	0.91	1.16	0.82	1.23	MBRatio
$MCap_{it}$	Log of Market capitalization (Rs. Billion, daily)	Prowess	13.38	12.55	13.05	13.23	13.26	14.13	MCap
$ShrTO_{it}$	Log of Share turnover (daily)	Prowess	14.91	15.04	15.14	14.08	14.63	15.20	ShrTO
$PInverse_{it}$	Log of Inverse of closing price (INR, daily)	Prowess	−5.82	−5.89	−5.57	−6.20	−5.79	−5.82	PInverse
# observations:	49 * 125 * 22,500 (stock * day * seconds)								

3.2. Variables construction

We use the $Size_{it}$ to capture the trade size based on the traded quantity. $Size_{it}$ indicates the traded quantity in stock i in the time interval t. We measures AT as AT Intensity using the below equation:

$$\boldsymbol{AT}_{\boldsymbol{Intensity}} = \frac{TTV_{AT,i,t}}{TTV_{i,t}} x100 \tag{1}$$

where, $TTV_{AT,i,t}$ refers to total traded volume in a stock (i) by AT in the time interval (t) and $TTV_{i,t}$ refers to total traded volume in a stock (i) in the time interval (t).

We also measure Algorithmic Trading Efficiency as $\boldsymbol{OTR_{it}}$ and define it as the number of orders placed (Entry + Cancel + Modify) in the market divided by the number of trades that got executed for the stock i in the time interval t.

$$\boldsymbol{OTR_{it}} = \frac{(OrdEntry_{it} + OrdCancel_{it} + OrdModify_{it})}{Trade_{it}} \tag{2}$$

We use control variables including log of market capitalization ($MCap_{it}$), log of market to book ratio ($MBRatio_{it}$), log of share turnover ($ShrTO_{it}$) and log of 1/price ($PInverse_{it}$) in our regression model. We also control for the stock fixed effects and time fixed effects. For robustness of our analysis we use Variance Inflation Factor (VIF Test) and find all VIF values to be<2 for all our variables.

$$MCap_{it} = OS_i \times P_t \tag{3}$$

Market capitalization is captured at the specific time t for the stock i by taking a product of total shares outstanding and price of the stock i at the time t.

$$MBRatio_{it} = MCap_{it}\tilde{\text{A}}\cdot BV_{it} \tag{4}$$

Market to book ratio is obtained by taking a ratio of Market capitalization of the stock i at time t and Book Value of the stock i from the financial statements obtained from Centre for Monitoring Indian Economy (CMIE) prowess database.

$$ShrTO_{it} = nS_{it} \tag{5}$$

Share-turnover is identified by the number of shares of stock i traded at time t.

$$PInverse_{it} = 1/P_{it} \tag{6}$$

Price inverse measure takes inverse of the share price of the stock i at time t.

These control variables are widely accepted in the existing literature (Aggarwal & Thomas, 2014; Goyenko et al., 2009; Hendershott et al., 2011; Kang & Zhang, 2014).

4. Hypothesis Formulation, results and discussion

We investigate the impact of AT and OTR on the trade size. The size variable is captured from the trades data which captures information up to milliseconds' interval. For our analysis, we also sort the stocks into quintiles (quintile 1 corresponds to small cap stocks and quintile 5 corresponds to large cap stocks) based on market capitalization and we also create another segregation and categorize them into large cap, mid cap and small cap stocks. We report the definitions of our measured variables and descriptive statistics in Tables 1 and 2.

Table 2
Descriptive statistics.

Variables	Mean[@]	Std. Dev	Minimum[@]	Maximum[@]
TradeSize	66	1428	1	$204x10^5$
MBRatio	1	0.91	0	4
ShrTO	15	1.06	8	18
PInverse	−6	0.83	−7	−3
AT_Intensity	70	4.71	35	79
OTR	23	51.89	0	3313

#Observations: 49*125*22500 (stock * trading days * seconds) ([@]Rounding Off to Nearest Integer, [$]- sign indicates buy side dominance)

Hendershott and Riordan (2013) and Hendershott et al. (2011) in their study indicate that AT is more active in smaller trade(size) categories. Since we have the direct identification of AT it would be interesting to see if the findings are consistent with previous studies. Therefore, we investigate the relationship between OTR, AT and $Size_{it}$ using the following regression equations:

$$Size_{it} = \alpha_{it} + \gamma_{it} + \beta AT_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it} \tag{7}$$

$$Size_{it} = \alpha_{it} + \gamma_{it} + \beta OTR_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it} \tag{8}$$

where $Size_{it}$ is trade size (traded quantity) measures for stock i in second t of the trading day.

We run regression analysis at 5 different levels with OTR and AT being regressed on trade size for 1) The overall sample, 2) Quintile wise, 3) Small, Mid and Large cap categorization wise, 4) Fama-MacBeth regression (date-wise) and 5) Fama-MacBeth regression (stock-wise). We use control variables including log of market capitalization ($MCap_{it}$), log of market to book ratio ($MBRatio_{it}$), log of share turnover ($ShrTO_{it}$) and log of 1/price ($PInverse_{it}$) in our regression model to control for their impact on the price discovery measures. We also control for the stock fixed effects and time fixed effects. We test the following Hypothesis using the above equations (Eqs. (7) and (8)) by examining the significance of coefficient β:

Hypothesis 1: Algorithmic Trading Intensity is inversely related to trade size
Hypothesis 1a: For the Nifty50 stocks, trade sizes decline with increase in algorithmic trading intensity

Table 3
Impact of Algorithmic Trading on Size (Traded Quantity, TrdQty).

Panel A: Coefficient of AT/OTR and other Control Variables when regressed on $Size_{it}$

	($\times10^{-4}$/bps)	$MCap_{it}$	$MBRatio_{it}$	$ShrTO_{it}$	$PInverse_{it}$
AT_{it}	−2375.0115***	−23.3735***	10.4097***	31.6454***	25.1957***
OTR_{it}	−120.0529***	−24.7213***	9.4591***	32.5004***	25.5749***

Panel B: Coefficient of AT/OTR when regressed on $Size_{it}$ (Quintile Wise, Q5 being the largest market cap)

($x10^{-4}$/bps)	Q1	Q2	Q3	Q4	Q5	Small Cap	Mid Cap	Large Cap
AT_{it}	−131.548***	−1742.670***	−2788.814***	−2753.262***	−2593.265***	−1831.830***	−1999.116***	−2719.538***
OTR_{it}	80.768***	913.508***	6.792	−397.295***	20.415	360.6165***	−318.0795***	−386.8429***

observations: 49 * 125 * 22,500 (stock * day * seconds)
P-value: <0.0001

This table shows the impact of algorithmic trading (AT Intensity) and algorithmic trading efficiency (OTR) on trade size variable. The table regresses the traded quantity on our algorithmic trading measure. It is based on 1 s observations for Nifty 50 stocks from March 2013 to August 2013 which covers 2 quarters (6 months or 125 trading days) of high frequency data with precision of 1 jiffy (1 Second = 65536 jiffies). The algorithmic trading is directly identified by the flag provided by the stock exchange (NSE). The specification for examining the impact is:

$Size_{it} = \alpha_{it} + \gamma_{it} + \beta AT_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$

$Size_{it} = \alpha_{it} + \gamma_{it} + \beta OTR_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$

where $Size_{it}$ is trade size (traded quantity) measures for stock i in second t of the trading day. (The trading hours of NSE is from 9:15 am to 3:30 pm which essentially means 6 h 15 mins or 22,500 s.) AT_{it} is the algorithmic trading intensity for the stock i in second t of the trading day (where, AT Intensity is measured as ratio of total traded volume in a stock i by AT in the time interval t to total traded volume in a stock i in the time interval t (Aggarwal & Thomas, 2014)). We also use a vector of control variables including log of market capitalization ($MCap_{it}$), log of market to book ratio ($MBRatio_{it}$), log of share turnover ($ShrTO_{it}$) and log of 1/price ($PInverse_{it}$). We also include stock fixed effects and time fixed effects. t-values are also examined as they are based on standard errors that are robust to general cross section and time-series heteroscedasticity and within group autocorrelation (Arellano and Bond, 1991). */**/*** denote significance at 10%/5%/1% level.

Table 4
Impact of Algorithmic Trading on Size (Fama-MacBeth Regression, date – wise).

Fama-MacBeth Regression Coefficient of AT/OTR and other Control Variables when regressed on $Size_{it}$ (date-wise)

	($x10^{-4}$/bps)	$MCap_{it}$	$MBRatio_{it}$	$ShrTO_{it}$	$PInverse_{it}$
AT_{it}	−2140.9670***	−23.2273***	10.3725***	33.3649***	22.2807***
OTR_{it}	−126.5610***	−24.4858***	9.4434***	34.4366***	22.4879***

observations: 125 trading days
P-value: <0.0001

This table shows the impact of algorithmic trading (AT Intensity//OTR) on size variable and summarizes date wise Fama-MacBeth regression results. The Fama-MacBeth (Fama & MacBeth, 1973; Opler et al., 1999) model gives the average of the time series of the coefficients from date-wise (N = 125) cross section regressions. The cross-sectional regression is estimated for each stock for the 125 trading days. The cross-sectional regression is based on 1 s observations for Nifty 50 stocks from March 2013 to August 2013 which covers 2 quarters (6 months or 125 trading days). The model specification for the cross-sectional regression is:

$Size_{it} = \alpha_{it} + \gamma_{it} + \beta AT_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$

$Size_{it} = \alpha_{it} + \gamma_{it} + \beta OTR_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$

where $Size_{it}$ is trade size (traded quantity) measures for stock i in second t of the trading day. (The trading hours of NSE is from 9:15 am to 3:30 pm which essentially means 6 h 15 mins or 22,500 s.) AT_{it} is the algorithmic trading intensity for the stock i in second t of the trading day (where, AT Intensity is measured as ratio of total traded volume in a stock i by AT in the time interval t to total traded volume in a stock i in the time interval t (Aggarwal & Thomas, 2014)). We also use a vector of control variables including log of market capitalization ($MCap_{it}$), log of market to book ratio ($MBRatio_{it}$), log of share turnover ($ShrTO_{it}$) and log of 1/price ($PInverse_{it}$). We also include stock fixed effects and time fixed effects. t-values are also examined as they are based on standard errors that are robust to general cross section and time-series heteroscedasticity and within group autocorrelation (Arellano and Bond, 1991). */**/*** denote significance at 10%/5%/1% level.

Hypothesis 1b: For the Nifty50 stocks, large cap stocks exhibit higher algorithmic trading intensity

Hypothesis 2: Algorithmic Trading Efficiency (1/OTR) is inversely related to trade size

Hypothesis 2a: For the Nifty50 stocks, trade sizes decline with increase in algorithmic trading efficiency

Hypothesis 2b: For the Nifty50 stocks, large cap stocks exhibit higher algorithmic trading efficiency

Tables 3–5 reports the results for the regression model specified above to indicate the impact of algorithmic trading efficiency and algorithmic trading intensity on the trade size. The most important coefficient of our interest is $\boldsymbol{\beta}$ **of** $\boldsymbol{OTR_{it}}$ and $\boldsymbol{\beta}$ **of** $\boldsymbol{AT_{it}}$ for each of the regression equations. Since we are expecting the trade size to be inversely related to algorithmic trading efficiency (1/OTR) and algorithmic trading intensity (AT), we expect the signs of coefficients for OTR to be positive and AT to be negative. However, from the Table 3 (Panel A), we observe that there is a significant impact of AT and OTR on the trade size, but the signs of the coefficients are not as expected. We observe that the coefficient of AT is −2375.0115 ($x10^{-4}$) which essentially means that with a unit rise in AT intensity, the trade size is expected to decline by 2375.0115 basis points. So, similar to existing studies we do find significant impact of AT on trade sizes and we also confirm the decline in trade sizes with increase in AT intensity. The Table 3 (Panel B) also reports the negative coefficient (−120.0529) of OTR with respect to trade size. Though we expected the trade sizes to decline with decline in OTR thereby indicating with higher algorithmic trading efficiency, the size of the trades decline. However, on aggregate level we find the result otherwise. The possible argument for this finding may be attributed to the quantum of AT orders being placed and therefore, most of the orders having smaller order quantities and thereby facilitating trades in smaller trade size categories. Therefore, even though the order-to-trade ratio is increasing, the disposable order quantities on an average are smaller and hence the trade sizes are also

Table 5
Impact of Algorithmic Trading on Size (Fama-MacBeth Regression, stock – wise).

Fama-MacBeth Regression Coefficient of AT/OTR and other Control Variables when regressed on $Size_{it}$ (stock-wise)					
	(x10^{-4}/bps)	$MCap_{it}$	$MBRatio_{it}$	$ShrTO_{it}$	$PInverse_{it}$
AT_{it}	−2488.480***	−20.5242	11.0189	18.2134***	−6.3720
OTR_{it}	3820.970***	−124.4336	11.2169	18.3622***	−117.5258
# observations: 49 stocks					
P-value: <0.0001					

This table shows the impact of algorithmic trading (AT Intensity/OTR) on size variable and summarizes stock wise Fama-MacBeth regression results. The Fama-MacBeth (Fama & MacBeth, 1973; Opler et al., 1999) model gives the average of the time series of the coefficients from stock-wise (N = 49) cross section regressions. The cross-sectional regression is estimated for each stock for the 125 trading days. The cross-sectional regression is based on 1 s observations for Nifty 50 stocks from March 2013 to August 2013 which covers 2 quarters (6 months or 125 trading days). The model specification for the cross-sectional regression is:

$$Size_{it} = \alpha_{it} + \gamma_{it} + \beta AT_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$$

$$Size_{it} = \alpha_{it} + \gamma_{it} + \beta OTR_{it} + \delta_1 MCap_{it} + \delta_2 MBRatio_{it} + \delta_3 ShrTO_{it} + \delta_4 PInverse_{it} + \varepsilon_{it}$$

where $Size_{it}$ is trade size (traded quantity) measures for stock i in second t of the trading day. (The trading hours of NSE is from 9:15 am to 3:30 pm which essentially means 6 h 15 mins or 22,500 s.) AT_{it} is the algorithmic trading intensity for the stock i in second t of the trading day (where, AT Intensity is measured as ratio of total traded volume in a stock i by AT in the time interval t to total traded volume in a stock i in the time interval t (Aggarwal & Thomas, 2014)). We also use a vector of control variables including log of market capitalization ($MCap_{it}$), log of market to book ratio ($MBRatio_{it}$), log of share turnover ($ShrTO_{it}$) and log of 1/price ($PInverse_{it}$). We also include stock fixed effects and time fixed effects. t-values are also examined as they are based on standard errors that are robust to general cross section and time-series heteroscedasticity and within group autocorrelation (Arellano and Bond, 1991). */**/*** denote significance at 10%/5%/1% level.

smaller. When we further examine the relationship between size and AT/OTR with respect to quintiles, we find that AT is significantly leading to reduction in trade sizes across all quintiles (see Table 3 Panel B). However, OTR was found to impact the trade sizes significantly only for Q1, Q2 and Q4. Surprisingly, we find algorithmic trading efficiency (1/OTR) to be inversely related to trade sizes for smaller quintiles (Q1 and Q2), however for Q4 it seems with rise in OTR (decline in algorithmic trading efficiency) the trade size declines. The possible argument supporting this finding could be the overall number of orders in the large cap quintiles and if most of the order size of algo is relatively smaller, we are bound to find lower trade size as well.

We further investigate the date-wise (daily) impact of OTR and AT on trade sizes. To examine the date-wise (daily) impact we use the Fama-MacBeth (Fama & MacBeth, 1973; Opler et al., 1999) model which gives the average of the time series of the coefficients from daily (date-wise, N = 125) cross section regressions. The cross-sectional regression is estimated for each trading day. The findings are presented in Table 4 and we observe that both AT and OTR have negative coefficients which essentially means decline in trade size with rise in AT intensity and decline in trade size with rise in order-to-trade ratio respectively. Both the coefficients are significant and the sign of the coefficient of AT is as expected, however the sign of the coefficient of OTR is positive for the possible reasons of overall executable order sizes floated by AT being small.

Similar to the date-wise (daily) impact we examine the stock-wise impact of OTR and AT on trade sizes. To examine the stock-wise impact we use the same Fama-MacBeth (Fama & MacBeth, 1973; Opler et al., 1999) model which gives the average of the time series of the coefficients from stock-wise (N = 49) cross section regressions. The cross-sectional regression is estimated for each stock for the entire 125 trading days. And the findings are presented in Table 5 which summarizes the stock-wise Fama-MacBeth regression results. We find that both AT and OTR significantly impact the trade sizes and on an average for each stock with rise in AT intensity and rise in algorithmic trading efficiency (decline in OTR) the trade size decreases by 2488.480 basis points and 3820.970 basis points respectively. Clearly, we find that in our stock wise analysis algorithmic trading efficiency (1/OTR) and algorithmic trading intensity are inversely related to trade size.

5. Conclusion

The existing literature only discusses about the impact of algorithmic trading; however, the algorithmic trading efficiency has been neglected mostly. We define inverse of order-to-trade ratio (OTR) as a measure of algorithmic trading efficiency and then further examine its impact on the trade size. We find evidence on the inverse relationship between trade size and algorithmic trading intensity and algorithmic trading efficiency. Drawing from the exiting literature and logical reasoning for wide acceptance of AT across the globe, we expected the trade sizes to decline with increased AT intensity and algorithmic trading efficiency. From our analysis, we concur with the findings of the existing literature that the AT and OTR's impact is significant on the trade sizes. AT is also found to be consistently leading to reduced trade sizes, in our aggregate level, quintile wise, date wise and stock wise analysis. However, the OTR measure has shown inverse relationship with trade sizes in all our analysis except the quintile wise, where we find that for the smallest two quintiles, OTR is directly proportional to the trade sizes indicating algorithmic trading efficiency is leading to decline in trading sizes for small cap stocks only.

The findings of our study have both theoretical and practical implications. Our study is one of the few studies with direct identification of AT and therefore it adds value to the existing body of literature. Our study also devises a novel way for measuring algorithmic trading efficiency. In the existing body of literature, there is lack of studies pertaining to studying the impact of AT in emerging order driven markets, as most of the studies are in developed quote driven market. The order driven markets and quote driven markets differ in the way liquidity is supplied in the market. This makes it even more interesting to examine the impact of AT in emerging order driven markets as AT is expected to provide liquidity unlike to developed quote driven markets which have designated market makers for the same. Future research in this field can be extended to examine the trading strategies of algorithmic traders and also on developing efficient algorithms for improving the market efficiency. Regulatory aspect regarding the impact of penalties with respect to higher order-to-trade ratios on AT behaviour, use of circuit breakers, profitability of AT, etc. can also be examined for further research.

Future research in the field may also be conducted using a recent data period to validate the current study's findings in the present-day scenario and to build upon the existing findings and explore other aspects and impacts of the expert systems (Algorithmic Trading Systems, ATS). However, the current study's findings do stand the test of time, and the same is observed from the views presented by ET[2] Contributors (2021). The ET Contributors (2021) highlights that the current share of AT by volume is about 50% in India, and *"In the coming years, Algo will capture market share in excess of 95 percent with volume growing many folds. So, the future of trading is Algo, and Algo is the future."* The observations align with the findings obtained from the dataset used for this study and Dubey (2016), Dubey et al. (2017, 2021), where they highlight above 95% trading by volume Nifty50 stocks. In due course, with

[2] ET Contributors. (2021, August 22). How algorithms are going to change the way you buy and sell stocks. Retrieved December 27, 2021, from The Economic Times website: https://economictimes.indiatimes.com/markets/stocks/news/how-algorithms-are-going-to-change-the-way-you-buy-and-sell-stocks/articleshow/85532682.cms

more adoption of AT by all market participants, the share of AT is bound to increase in all listed stocks and will not be limited to just large-cap liquid stocks. Executing large trades pose a price impact that hurts price discovery, and therefore the findings of this study highlight that the role played by these intelligent systems (AT) to break the large trades into smaller trade sizes is well aligned with the expectations of the market regulators and traders.

CRediT authorship contribution statement

Ritesh Kumar Dubey: Conceptualization, Methodology, Software, Data curation, Writing – original draft, Visualization, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I. Data-structure of dataset obtained from NSE DOTEX

Orders Data Set	Var. Constructed	Trades Data Set	Var. Constructed
1. Record Indicator (RM/PO)[2]		1. Record Indicator (RM/PO)	
2. Segment (Cash)		2. Segment (Cash)	
3. Order Number		3. Trade Number	
4. Transaction Time (Jiffies)[3]	**OrdTime**	4. Trade Time (Jiffies)	**TrdTime**
5. Buy/Sell Indicator	**QS, PQS**	5. Symbol (NSE)	
6. Activity Type (Entry/Mod/Can)	**QS, PQS**	6. Series (EQ)	
7. Symbol (NSE)		7. Trade Price	**TrdPrice, QS**
8. Series (EQ)		8. Trade Quantity	**TrdQty**
9. Volume Disclosed		9. Buy Order Number	
10. Volume Original	**OQty**	10. Buy Algo Indicator	**AT_Intensity**
11. Limit Price	**OrdPrice, QS**	11. Buy Client Identity Flag	
12. Trigger price		12. Sell Order Number	
13. Market Order Flag	**MLOrdInd**	13. Sell Algo Indicator	**AT_Intensity**
14. Stop Loss Flag		14. Sell Client Identity Flag	
15. IO Flag	**IOC_Flag**		
16. Algo Indicator	**AT_Intensity**		
17. Client Identity Flag			

[2] RM refers to regular market and PO refers to pre-open market.
[3] 1 Second = 65536 Jiffies.

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