# The causal impact of algorithmic trading on market quality

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July 2014

**Abstract**

What is the impact of algorithmic trading (AT) on market quality? This research question has been dogged by endogeneity bias. We address the problem by using orders clearly identified as originating from AT, and the introduction of co-location as an exogenous event after which AT increased. A matched set of firms with high and low AT activity are identified for use in a difference-in-difference regression to estimate causal impact. Securities with higher AT have lower liquidity costs, order imbalance, and price volatility. We offer new evidence that higher AT is not associated with higher intraday liquidity risk or higher incidence of extreme intraday price movements.

*JEL classification*: G10, G18
*Keywords*: Electronic limit order book markets, matching, difference-in-difference, efficiency, liquidity, volatility, flash crashes

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# Contents

# 1 Introduction

Technology has played an increasingly important role in the development of securities markets since the 1990s. Though it was readily embraced in the back-end functions of clearing and settlement at exchanges, it played a more controversial role in its implementation in trading processes. In the 1970s, there was much debate about moving from open outcry markets to electronic limit order book markets. The latter became accepted as the dominant form of trading only in the last decade. A similar controversy surrounds algorithmic trading (AT) in exchanges, where computer algorithms directly place orders to trade. Policy makers, who largely encouraged the use of technology by mandating best execution practices for investors in the 1990s, are now exploring interventions to curb high frequency trading, in 2010s.

Several papers have been written on the subject. However, the analyses have faced challenges in establishing causal linkages between changes in AT and changes in market quality (Biais and Foucault, 2014). This paper sets out to address some of these challenges using a novel dataset and market setting.

The first amongst these challenges is fragmented trading. In markets such as those in the U.S., which is the focus of most of the research work in this field, trading takes place at numerous venues, each with varying market access and microstructure. The analysis of any one trading venue is limited as traders have positions on many markets, and the appropriate measure of market quality is at the level of the overall financial system rather than any one trading venue (Biais and Foucault, 2014).

A second challenge is the lack of clear identification of the orders and trades generated by algorithms. Much of the existing research is based on proxies of AT which leads to weak identification (Hendershott *et al.*, 2011; Hasbrouck and Saar, 2013). Where there is better identification, the datasets are restrictive. Either the sample of securities is limited, or the period under study is short (Hendershott and Riordan, 2013).

A third challenge is in establishing causality. This problem arises because of the unobserved factors which affect can algorithmic trading as well as market quality on a security at the same time.

This paper has three advantages in establishing a causal link between AT and changes in market quality. First, it uses data from the National Stock Exchange (NSE), India, on which 75% of the country's equity spot trading and 100% of the derivatives trading is concentrated during the period of the analysis. This mitigates the problems related to fragmented trading. Second, it utilises a proprietary tick by tick dataset spanning a period between 2009 and 2013, on all securities traded on the NSE. The dataset contains an AT flag for each order and trader, indicating whether the order or a trade was from an AT or a non AT.

Third, to address endogeneity issues, the paper uses an exogenous event when the exchange commissioned co-location facilities (*co-lo*). This event directly affected the level of algorithmic trading, but not market quality. Based on this event, we divide the sample into pre *co-lo* and post *co-lo* periods, and analyse the change in market quality of matched securities.

We then use a propensity score matching algorithm to identify pairs of securities that are matched on firm characteristics such as size, price, turnover, floating stock, but differ in the level of AT. The securities which experienced a large change in the level of AT activity after *co-lo* are the treated group. The control group are securities with AT activity that were similar to the treated securities before *co-lo*, but did not show a significant change in AT activity after *co-lo*. A difference-in-difference regression is used to estimate the change in market quality of the treated relative to control securities. Significant differences between the two can be attributed to higher level of AT. We also control for changes in macroeconomic conditions by matching dates in the pre *co-lo* and post *co-lo* periods with similar levels of market volatility. This ensures comparability across the two periods without requiring assumptions about functional forms to be used as regression-style controls.

The results of our analysis suggest that, on an average, higher AT results in better market quality of a traded security. This includes lower spreads and impact costs, larger number of shares available for trade, lower imbalance between the number of shares available to buy and sell, and a sharp drop in price volatility. The depth (measured by the monetary value available to trade) is not significantly affected by higher AT at the touch (best bid and offer).

This paper adds new evidence to the literature about the causal impact of AT on the stability of prices and liquidity. Policy makers and regulators often voice concerns that the higher level of liquidity is transient because AT exits the market rapidly when there is unexpected news. Their main criticism is that AT causes a higher probability of extreme drops and reversals over a very short period of time during the trading day (Chordia *et al.*, 2013). The estimates in this paper show that AT *lowers* intraday liquidity risk. It also shows that higher AT leads to a *lower* incidence of extreme price movements during the trading day.

Thus, the contribution of this paper lies in going closer to a causal analysis of the impact of algorithmic trading upon market quality. The analysis uses a high quality dataset with a large span of time and securities. In addition to well-studied measures of liquidity and volatility, the paper also uncovers new evidence about intra-day flash crashes and intra-day liquidity risk.

The remainder of the paper is organised as follows: Section 2 summarises the literature. Section 3 provides a brief detail on the institutional framework. Section 4 discusses the identification of algorithmic trading activity and various market quality measures. Section 5 describes the approach used for analysis in detail. Section 6 describes the process of sample selection, and presents summary statistics about the final sample. Section 7 presents the estimation results, followed by Section 8 which tests the robustness of the estimates. Section 9 concludes.

# 2 Algorithmic trading and market quality

The rapidly expanding literature on algorithmic trading (AT) focuses on whether such trading enhances the ability of markets to improve long term investors' welfare and capital efficiency for firms. Theory suggests that high frequency trading, a subset of AT, can have both positive and negative impact. The positive impact lies in a rapid transmission of information into market prices (Jovanovic and Menkveld, 2010; Martinez and Rosu, 2013), and improvement in market liquidity (Hoffmann, 2012; Foucault, 1999). However, the negative effect of higher AT could be an increase in the adverse selection costs for non-algorithmic traders(Biais *et al.*, 2013; Cartea and Penalva, 2012), or higher systemic risk due to higher probability of 'flash crashes'.

The empirical research has got a wider consensus. A higher presence of AT is found to be associated with lower costs of liquidity as well as lower short term volatility (Hendershott *et al.*, 2011; Hasbrouck and Saar, 2013). Others find higher price efficiency and liquidity with higher levels of HFT, particularly around times of market stress (Menkveld, 2013; Carrion, 2013; Brogaard *et al.*, 2012; Chaboud *et al.*, 2009), and that AT demands liquidity when it is cheap and supplies it when scarce (Hendershott and Riordan, 2013; Carrion, 2013).

This literature however comes with well documented limitations (Biais and Foucault, 2014). One limitation being much of the empirical analysis is done based on proxies to identify an AT order/trade. Recent data has better identification but are restricted to either very few securities or a short period of time. For example, Hendershott and Riordan (2013) studies 30 DAX securities for 13 days.

A greater limitation is that the literature has not readily established causal links between AT and market quality because of the inherent endogeneity between the two. This makes it difficult to determine the direction of causality. For example, in case of an information event, there can simultaneously be an increase in AT activity on a security and an increase in the observed market liquidity. The common factor – information arrival – is what causes the change in both. It would be misleading to make a causal inference based purely on a high correlation between AT and market liquidity in this case.

One approach to counter this endogeneity bias is to use an exogenous event that is expected to directly affect the extent of AT, but not market liquidity. These events are then used as instruments for AT to identify the direction of causality between AT and the market quality variable. For example, Riordan and Storkenmaier (2012) analyse the effect of a drop in latency at the Deutsche Bourse, and find the event is correlated with decreased spreads and higher price efficiency.[1] Bohemer *et al.* (2012) use the introduction of co-location on 39 exchanges worldwide, and find that higher AT is correlated with higher market liquidity and efficiency.

While these approaches strengthen the argument regarding the links between higher AT and better market quality, the community of policy makers and practitioners remain unconvinced and mistrustful of the role of AT. Amongst the reasons lie these two major limitations of restricted datasets and endogeneity issues. In this paper, we present a research setting that uses a market microstructure with a unique dataset and a robust econometric framework to counter these issues.

# 3 Research setting

This paper draws on three strengths. First, it uses a microstructure setting where most spot trading and all derivatives trading takes place at one exchange. Second, the underlying data infrastructure precisely flags every order and the counterparties of every trade as coming from an algorithmic source

[1]Studies such as Viljoen *et al.* (2011), Frino *et al.* (2013) also examine the impact of AT on the futures market around such events and find a positive effect of AT on market quality.

(marked AT) or not. Third, it uses the exogenous event when co-location facilities were introduced on the exchange, and market quality can be measured and analysed both before and after this event on matched securities.

## 3.1 A clean microstructure

We analyse the impact of AT on market quality on one of the three exchanges[2] trading equity in India: the National Stock Exchange (NSE). NSE is one of the highest ranked equity markets in the world in terms of transaction intensity (WFE, 2012). Unlike in the U.S., where equity trading is fragmented across multiple platforms, NSE has the largest share of the equity market activity in India.[3] These features help to address one of the limitations pointed out by Biais and Foucault (2014), that most of the existing studies rely on a single market or a single asset, and that the lack of cross-market data can affect inference because high frequency traders are likely to take positions in multiple markets at the same time.

The NSE spot market is an electronic limit order book market, which trades around 1500 securities. All trades are cleared with netting by novation at the clearing corporation and settled on a $T+2$ basis. Trades that are offset within the day account for roughly 70% of the turnover. Of the trades that are settled, typically around 10-15% are done by institutional investors. Thus, most of the trading can be attributed to retail investors or proprietary trading by securities firms.

## 3.2 A unique dataset

Our analysis uses tick by tick dataset of all equity orders and trades from the NSE for a five-year period from 2009 to 2013. NSE disseminates information about trades and orders, with prices and quantities that are time-stamped to jiffies. In addition to other information,[4] each order and trade is also tagged with an AT flag that allows us to identify if the order/trade originated from

[2] The other two are the Bombay Stock Exchange and Multi-commodity Stock Exchange.

[3] 75% of the traded volumes on the Indian equity spot market and 100% of the traded volume on equity derivatives took place on NSE during the period of our analysis (SEBI, 2013).

[4] This includes tags for special orders such as "Stop-Loss", "Immediate Or Cancel" and "Hidden orders".

AT or non-AT.[5]

This is in contrast to the prior literature in which the impact of AT is observed by a proxy, either through electronic message traffic (Hendershott *et al.*, 2011; Bohemer *et al.*, 2012) or *RunsInProcess* as the number of linked messages (Hasbrouck and Saar, 2013). The closest direct measure of algorithmic trading is where the exchange identifies trading firms as 'engaging primarily in high frequency trading', as used in Brogaard (2010); Brogaard *et al.* (2012); Carrion (2013). However, because the data are available only on 120 randomly selected securities that the high frequency firms trade in, these do not comprise the comprehensive set of all high frequency trades in the market. Another example is described in Hendershott and Riordan (2013), which uses data containing all AT orders on the German exchange DAX but include 30 securities over 13 trading days.

In comparison to these samples, the data from NSE are not so restricted; all securities for the entire period are covered with a long horizon.

## 3.3 An exogenous event: Introduction of co-location facilities

Automated order placement began in India with a few securities firms that used technology for equity spot arbitrage between the NSE and the Bombay Stock Exchange (BSE). Even after the securities regulator issued regulations governing AT in April 2008 (SEBI (2008)), the level of AT remained low.[6]

A significant change in the amount of AT came after the introduction of co-location facilities at the NSE in January 2010, suggesting that the earlier technology was a bottleneck to effective AT. After co-location was introduced, latency dropped from 10-30 ms (milliseconds) to 2-6 ms, giving traders who established automated systems in the co-location facility a significant edge. This clear shift in technology on a well-identified date serves as an identification mechanism to analyse changes in market quality in a period when there was higher AT presence versus a period when it was low.

[5] The identification is done at the level of the I.P. address of the computer from where the order is generated.

[6] *Indian markets slowly warming up to algorithmic trading*, The Mint, July 14 2009.

# 4 Measurement

In this section, we first describe the measurement of AT intensity on a security/market followed by measures of market quality computed from the orders and trades data.

## 4.1 AT intensity

We use trades data to calculate the AT activity for a security based on the value of trades, where the algorithmic trader can be the buyer or the seller, or both. This is calculated over a fixed interval of time within the trading day to obtain AT-INTENSITY, a discrete measure of the AT activity for a security.

$\text{AT-INTENSITY}_{i,t}$ is calculated as the fraction of the AT trades in security $i$ taking place within a five-minute interval as

$$\text{AT-INTENSITY}_{i,t} = 100 \times \frac{\text{TTV}_{AT,i,t}}{\text{TTV}_{i,t}}$$

where $\text{TTV}_{AT,i,t}$ is the traded value of AT trades in the $t^{th}$ time interval and $\text{TTV}_{i,t}$ is the total traded value of all trades in the same period.

## 4.2 Market quality

Access to high frequency data at the order level for each security allows for measures covering three dimensions of market quality: liquidity, volatility, and efficiency. While the measures of market liquidity and volatility are common with rest of the literature, this paper, to our knowledge is the first to analyse intraday volatility of liquidity and extreme price movements.

### 4.2.1 Liquidity

Market liquidity is measured in two dimensions, transactions costs and depth. Transactions costs denote the price of immediacy, measured as the cost of executing a market order, and are higher for less liquid markets. Depth measures the number of shares available for trade at any given point in time and is lower for less liquid markets.

With access to the full limit order book for a security, there are various levels at which the available depth can be measured. In keeping with the rest of the literature, we measure depth both as value of shares as well as number of shares available for trading.

**Transactions costs:**

a) Quoted Spread (QSPREAD): the difference between the best ask and the best bid price at any given point of time. The spread for security '$i$' at time '$t$', $\text{QSPREAD}_{i,t} = 100 \times \frac{(\text{P}_{\text{BestAsk}_{i,t}} - \text{P}_{\text{BestBid}_{i,t}})}{(\text{P}_{\text{BestAsk}_{i,t}} + \text{P}_{\text{BestBid}_{i,t}})/2}$

b) Impact Cost (IC): IC to measure the transaction cost for a market order of size $Q$ that is larger than what is available at the best price. $\text{IC}_{Q_{i,t}}$ for security $i$ at time $t$ is calculated as: $\text{IC}_{Q_{i,t}} = 100 \times \frac{\text{P}_{Q_{i,t}} - \text{P}_{\text{M}_{i,t}}}{\text{P}_{\text{M}_{i,t}}}$

   $\text{P}_{\text{BestAsk}_{i,t}}$ and $\text{P}_{\text{BestBid}_{i,t}}$ are the best ask and bid prices, respectively, at $t$. $\text{P}_{\text{Q}_{i,t}}$ is the execution price for a market order of $Q$, and $\text{P}_{\text{M}_{i,t}}$ is the mid-quote price. In our analysis, $Q$ = USD 500, or Rs 25,000, which is the average size of equity spot market transactions at NSE.

   More liquid the market is, lower are the transaction costs.

**Depth:**

c) The value available for trade at the best bid and ask price, $\text{TOP1DEPTH}_{i,t} = \text{P}_{\text{BestBid},i,t} \times \text{Q}_{\text{BestBid},i,t} + \text{P}_{\text{BestAsk},i,t} \times \text{Q}_{\text{BestAsk},i,t}$

d) The value available for trade at the best five bid and ask price, $\text{TOP5DEPTH}_{i,t} = \Sigma_{k=1}^{5} \text{P}_{\text{Bid},k,i,t} \times \text{Q}_{\text{Bid},k,i,t} + \Sigma_{k=1}^{5} \text{P}_{\text{Ask},k,i,t} \times \text{Q}_{\text{Ask},k,i,t}$

e) The total number of shares available for trade in the full limit order book for security $i$, $\text{DEPTH}_{i,t} = \frac{\text{TSQ}_{i,t} + \text{TBQ}_{i,t}}{2}$

f) The difference in the total number of shares available for buy and sell, $\text{OIB}_{i,t} = \frac{(\text{TSQ}_{i,t} - \text{TBQ}_{i,t}) \times 200}{\text{TBQ}_{i,t} + \text{TSQ}_{i,t}}$

   $\text{P}_{\text{BestAsk}_{i,t}}$ and $\text{P}_{\text{BestBid}_{i,t}}$ are the best ask and bid prices, respectively, of security '$i$' at time '$t$'. $\text{TSQ}_{i,t}$ is the total quantity of shares available on the sell side and $\text{TBQ}_{i,t}$ on the buy side.

   For TOP1DEPTH, TOP5DEPTH, and DEPTH, more liquid the market, larger the values of the measure. A more liquid market is assumed to be balanced between the quantity available for buy and sell transactions. A more liquid market is expected to have $\text{OIB} = 0$.

### 4.2.2 Risk

Two aspects of market risk are observed from the limit order book, price risk and liquidity risk. This allows for three measures of market risk:

g) Price risk (RVOL): The variance of intraday returns, where returns are calculated using traded prices at a frequency of one-second as:

$$\text{RVOL}_{i,t} = \sqrt{\frac{\Sigma_{j=1}^{300}(r_{i,t,j} - \overline{r}_{i,t})^2}{n-1}}$$

where '$t$' indexes the five-minute time interval within the trading day and '$j$' indexes one-second time intervals within each five-minute interval. $\overline{r}_{i,t}$ indicates the mean returns within the five-minute interval, $t$.

h) Price risk (RANGE): The difference between the highest and the lowest mid-quote in a five-minute interval, expressed as a percentage of the mid-quote price (Hasbrouck and Saar, 2013):

$$\text{RANGE}_{i,t} = 100 \times \frac{\text{Max}(\text{P}_{i,t}) - \text{Min}(\text{P}_{i,t})}{\text{P}_{\text{M}_{i,t}}}$$

where '$t$' indexes the five-minute time interval within the trading day, $\text{Max}(\text{P}_{i,t})$ indicates the maximum price of security 'i' interval 't', $\text{Min}(\text{P}_{i,t})$ indicates the minimum price of that security in that interval, and $\text{P}_{\text{M}_{i,t}}$ indicates the mid-quote price of that security in the same interval.

The RANGE provides a robustness check on the RVOL.

i) Liquidity risk (LRISK): The volatility of the impact cost of transaction of a fixed size, $Q$. Since the impact cost can be measured at multiple time points during the trading day, we calculate the standard deviation of $\text{IC}(\text{Q})_{i,t}$ for five-minute intervals. This measures the intraday *liquidity risk.*

$$\text{LRISK}_{i,t} = \sqrt{\frac{\Sigma_{j=1}^{300}(\text{IC}_{i,j} - \overline{\text{IC}}_{i,t})^2}{n-1}}$$

'$t$' indexes the five-minute time interval, while $j$ indexes the one-second time points within interval $t$. $\overline{\text{IC}}_{i,t}$ is the average IC(Q) of the five-minute interval.

### 4.2.3 Efficiency

We use the variance ratio to measure market efficiency:

j) Variance Ratio (VR): The ratio of $1/k$ times the variance of the $k$-period return to the variance of the one-period return (Lo and MacKinlay, 1988). $\text{VR}(k)_i = \frac{\sigma^2[r_t(k)]}{k \cdot \sigma^2[r_t]}$

where $r_t$ is the one-period continuously compounded return, $r_t(k) = r_t + r_{t-1} \ldots + r_{t-k}$. $k$ indicates the lag at which the variance ratio (VR) is to be computed. In this paper, we calculate VR at $k = 2$. We do not expect VR to be significantly different from 1 in an efficient market.

### 4.2.4 Extreme price movements

A fear amongst policy makers is that AT causes higher price instability, which hurts investors. We measure this using the kurtosis of the returns.

k) Kurtosis (KURTOSIS): The incidence of extreme price movements. $\text{KURTOSIS}_{i,t} = \frac{\Sigma_{j=1}^{N}(r_{i,t,j} - \overline{r}_{i,t})^4}{(n-1)\sigma^4_{r_{i,t}}}$

where $r_{i,t,j}$ denotes the returns in the five-minute interval, 't' for each second, $j$ represents the observations within the interval from $1 \ldots N$, and $\sigma_{r_{i,t}}$ represents the standard deviation of returns in that five-minute interval. When the kurtosis is greater than 3, it indicates that the returns distribution has fatter tails, which implies a larger incidence of extreme price movements.

A higher tail risk will imply that the KURTOSIS value is significantly different from 3.

# 5 Research design

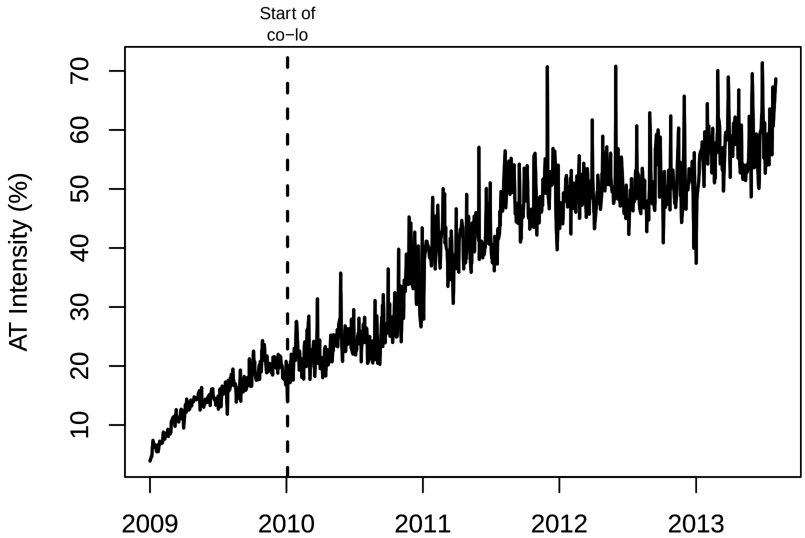
Two features of the research design address endogeniety bias. The first identifies an exogenous event that affects AT but not market quality and identifies the sample period chosen for the analysis. The second identifies pairs of securities that are matched except for the AT intensity and identifies the sample subset of securities.

## 5.1 Addressing endogeniety: selecting the sample period

Riordan and Storkenmaier (2012) and Bohemer *et al.* (2012) use an exogenous event as an instrument to identify periods where AT activity is different, but

**Figure 1** AT intensity between 2009 and 2013

The graph shows AT intensity on the equity spot market at NSE between 2009 and 2013. AT intensity is measured as a fraction of the total traded value of AT trades in a day vis-a-vis the total traded value on that day. The dotted line shows the date on which *co-lo* was introduced by NSE.



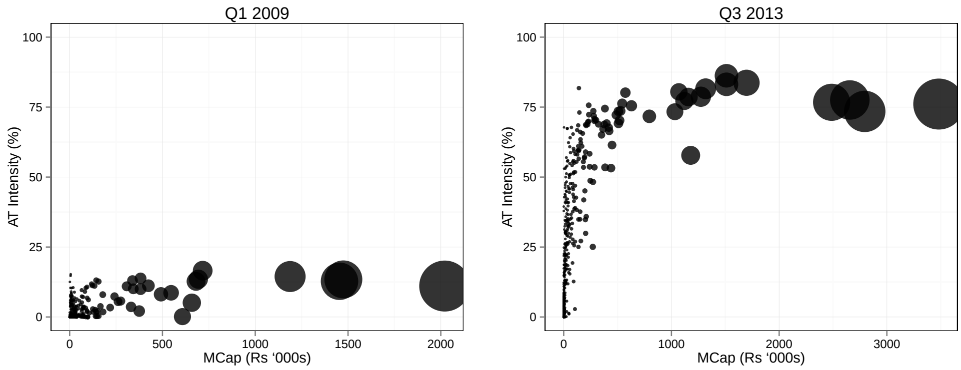

where market quality would otherwise be unchanged. We follow a similar approach. The NSE introduced co-location facilities (henceforth referred to as *co-lo*) in January 2010. The standard event study would analyse market quality changes immediately before and after this date. However, if different market participants adjust to the co-lo at a different pace, we expect that any change in AT intensity would stabilise after the overall market adoption of *co-lo*, much after its introduction. If the change in AT has not stabilised, related changes in market quality may not be fully measured.

Figure 1 plots the daily average AT intensity for the overall market, from 2009 to 2013. The AT intensity was around 20% before the introduction of the co-lo in January 2010 (marked by the vertical line in the graph). The AT intensity steadily increased between January 2010 and July 2011, when participants were adopting the new technology.

The adoption follows an S-curve, which clarifies that a sharply defined event study of a short period immediately before and after the introduction of co-lo may not reveal the full impact of AT on market quality. The growth of AT intensity stabilised at 50% only after July 2011, one and a half years after the introduction of co-lo. From Figure 1, we select the following two periods

**Figure 2** Cross sectional heterogeneity in AT intensity

The graph plots the daily average level of AT intensity in the *pre co-lo* and *post co-lo* periods, for each security in the sample period.
Each dot on the graph represents a security. The size of the dot is proportional to the market capitalisation of the security. While all the large dots (large firms) have uniformly moved from low AT intensity (close to the x-axis) in the *pre co-lo* period to far away in the *post co-lo* period, there is a significant cross-sectional variation in how AT intensity changed for the smaller dots (medium- and small-sized firms).




for our analysis:

- *pre co-lo*: January 1, 2009 to December 31, 2009 (260 days), where the data show a low level of AT intensity.
- *post co-lo*: July 1, 2012 to Aug 31, 2013 (291 days), where the AT intensity is significantly higher.

Endogeniety bias presents a critical barrier to causal inference on whether AT affects market quality. Securities with high market quality (such as high liquidity) are most likely to be more attractive to algorithmic traders. This complicates establishing whether AT intensity causes higher levels of market quality or whether other unobserved factors simultaneously cause high market quality and high AT intensity.

One strategy to establish causal links is to identify securities that are identical in every way, except for the level of AT activity they attract. For example, large-sized firms tend to be more liquid than small-sized firms. If a group of large-sized securities get higher AT activity after the introduction of co-location compared to another group of similarly sized large firms, any difference in market quality between the two groups can be attributed to AT.

Most of the large firms in our data (market capitalisation above Rs.0.5 million in Figure 2) saw a significant and *uniform* increase in the level of AT intensity. However, the change in AT intensity among the set of medium- and small-sized securities (market capitalisation less than Rs. half million) is heterogenous: some small- and medium-sized firms experienced a substantial increase in AT in the post co-lo period, while others saw a negligible change.[7] We exploit this observed cross-sectional heterogeneity in the AT intensity of these firms to identify a set of securities such that they have the following attributes:

1. *matched* in underlying characteristics that influence their market quality, but
2. *different* in the change of AT intensity in the *post co-lo* and *pre co-lo* periods.

## 5.2 Addressing endogeniety: selecting matched securities

The purpose of matching is to find pairs of securities that have similar characteristics in all aspects except in their response to the introduction of co-lo. One in the pair (called the "treated") ought to see a high increase in AT intensity, and the other (called the "control") ought to see a negligible change in AT intensity. The matching procedure used is as follows:[8]

**a)** Identify the covariates on which to match securities. These are called the *matching covariates*.

Typical matching covariates for firms include market capitalisation and the price (Davies and Kim, 2009). We further include floating stock, traded volume, and number of trades of the security to capture market characteristics as well. The securities are matched using the daily average value of each matching covariate in the *pre co-lo* period. We do not include the level of AT or any of the market quality variables to avoid any bias that may arise from variable selection based on estimated effects (Stuart, 2010).

**b)** Select a distance measure to test the quality of the match.

[7] The complete animation of the time series evolution of AT intensity across the sample securities is available at: `http://ifrogs.org/releases/ThomasAggarwal2014_algorithmicTradingImpact.html`

[8] Stuart (2010) provides a useful review of matching methods along with a summary of the literature.

We use the propensity score[9] to test the matching quality (Rosenbaum and Rubin, 1983). The propensity score for security $i$ is defined as the probability that $i$ will undergo the *treatment*, $T_i$, conditional on the set of observed covariates ($X$). In this case, the treatment is an increase in the AT intensity. If the propensity score for $i$ is defined as $e_i$:

$$\begin{aligned} e_i(X_i) &= P(T_i = 1|X_i) \quad \text{then,} \\ D_{ij} &= |e_i - e_j| \end{aligned}$$

where $D_{ij}$ is the distance measure between $i$, which is a treated security, and $j$ is the matched security that does not receive the treatment and is referred to as the control security.

The advantage of propensity score matching compared to alternatives, such as the exact or Mahalanobis distance measures, is that it helps to construct matched pairs that have similar distributions of covariates, without requiring close or exact matches on each covariate (Stuart, 2010).

**c)** Select a specific matching algorithm and match balance statistics.

Once we obtain the propensity scores, we match firms using the nearest neighbor matching algorithm *with* replacement and a caliper of 0.01.

## 5.3 Threats to validity: changes in the macro-economy

In Section 5.1, we identified the *pre co-lo* and *post co-lo* periods to estimate the impact of AT intensity. However, these two periods are separated by around 18 months, in which time there can be other factors (such as macro-economic changes) that can cause significant changes in market quality. For example, market volatility between the two periods could be different because of macro-economic changes rather than a change in AT intensity. The *pre co-lo* period follows immediately after the 2008 financial crisis, where market volatility was much higher than during the *post co-lo* period, which occurred well after the crisis.

A similar argument holds for liquidity. The literature on commonality of liquidity shows that the liquidity of individual equity is strongly correlated with market liquidity (Chordia *et al.*, 2000). In turn, market liquidity is strongly related to market volatility (Hameed *et al.*, 2010). A systematic difference in market volatility between the *pre co-lo* and *post co-lo* periods is likely to be manifested as a systematic difference in market liquidity between these periods as well.

[9] The propensity score is estimated using a logit model with the given set of covariates.

**Figure 3** Daily market volatility and monthly market liquidity, 2009 - 2013

The first graph below shows the daily time series of the implied volatility index, India VIX between 2009 and 2013, and the second graph shows the monthly time series of the impact cost of buying and selling Rs.5 million (under USD 80,000) worth of the NSE-50 index.
The dashed line indicates the date on which NSE started co-lo services. The period prior to the dashed line is the pre co-lo period (Jan 2009 - Dec 2009), while the period from July 2012 - Aug 2013 is the post co-lo period.

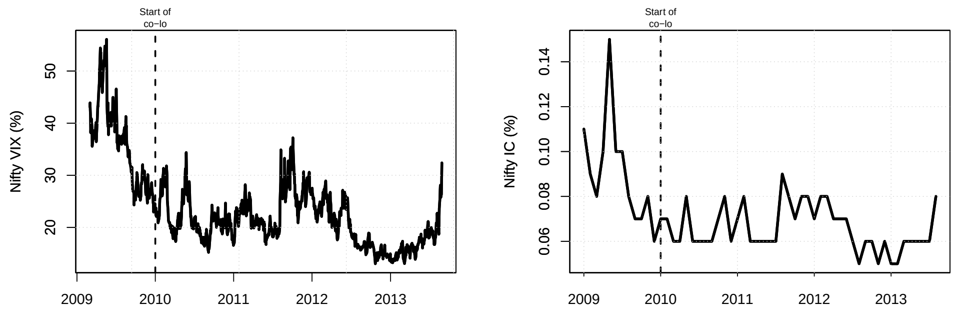



Figure 3 examines the time series of the volatility and liquidity of the market index, the NSE-50 or Nifty[10] between January 2009 and August 2013. Volatility is measured by the daily time series of the implied volatility index, India VIX.[11] Liquidity is measured by the monthly time series of the impact cost of the Nifty index[12] in the same period. Market volatility was much higher in the *pre co-lo* period compared to the *post co-lo* period. Similarly, the Nifty impact cost was also much higher higher (signifying lower market liquidity) during the *pre co-lo* period compared to the *post co-lo* period.

We adjust for macro-economic factors by restricting our analysis to a sample where the dates are matched on these factors in the *pre co-lo* and the *post co-lo* periods, so as to obtain robust inference.[13] Since market volatility

[10]Nifty is the market index comprising the 50 largest firms in terms of market capitalisation and transactions costs traded on the NSE.

[11]India VIX is a volatility index based on the Nifty index option prices. Nifty is NSE's market index based on 50 securities, which constitute about 70% of the free float market capitalisation of the securities listed on NSE. India VIX uses the Chicago Board Options Exchange (CBOE) computation methodology, with few amendments to suit the Indian markets (NSE).

[12]The impact cost of the index is the transaction cost incurred by a market order to either buy or sell the 50 securities in the Nifty index of a transaction size of Rs.50 lakhs (around USD 83,333.00). The Nifty impact cost values are disseminated by the NSE on a monthly basis.

[13]While matching methods are generally applied at the level of units of observations such as households or firms or countries, they can also be applied to choose time periods

captures macro-economic effects, we use only those dates in the *pre co-lo* and *post co-lo* periods that have the same level of market volatility.

## 5.4 The difference-in-differences regression (DID)

Given a sample with matched treated and control securities, for a set of dates in the *pre co-lo* and *post co-lo* periods that are matched on market volatility, we estimate the impact of AT on market quality using the following difference-in-difference (DID) regression:

$$\begin{aligned} \text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1 \text{AT}_i + \beta_2 \text{CO-LO}_t + \beta_3 \text{AT}_i \times \text{CO-LO}_t + \\ &\quad \beta_4 \text{NIFTY-VOL}_t + \beta_5 \text{INTRADAY-DUMMY}_t + \beta_6 \text{LTP}_{i,t} + \epsilon_{i,t} \end{aligned}$$

where $\text{MKT-QUALITY}_{i,t}$ indicates a market quality variable for security '$i$' at time '$t$'. $\text{AT}_i$ is a dummy that takes value 1 if $i$ belongs to the treatment group, 0 otherwise. $\text{CO-LO}_t$ is a dummy that takes value 1 if $t$ belongs to *post co-lo* period, 0 otherwise. We control for time-of-day effects by including $\text{INTRADAY-DUMMY}_t$, which takes on the value 1 if '$t$' is the first or the last half an hour of the trade, 0 otherwise.[14] In addition, we also control for market volatility, ($\text{NIFTY-VOL}_t$), which is the variance of five-minute returns on the market index and price of the security ($\text{LTP}_{i,t}$) within the interval.

The advantage of difference-in-differences compared to a simple event study analysis is that it not only eliminates the differences due to the event (*pre co-lo* versus *post co-lo*) but also adjusts for the differences in the treatment and the control group.[15]

The coefficient of interest is $\beta_3$, on the interaction term ($\text{AT}_i \times \text{CO-LO}_t$). The sign and the value of $\hat{\beta}_3$ is the estimate of the treatment effect (Meyer, 1995), which in our case is high AT. A significant value of $\beta_3$ indicates that AT causes market quality. $\beta_3$ will be zero in the absence of any impact of AT intensity. We test the hypothesis ($\text{H}_0^1$):

$$H_0^1 : \beta_3 = 0$$
$$H_A^1 : \beta_3 < 0$$

for all values of MKT-QUALITY $\in$ (QSPREAD, IC, LRISK, |OIB|, RVOL). If higher AT intensity results in better market quality, we expect $\beta_3$ to be

that are similar (Moura *et al.*, 2013).

[14] The inclusion of the first and the last half hour adjusts for the U-shape of market volatility during the trading day documented in the literature (Thomas, 2010).

[15] The coefficient capturing the differences in the treatment and control group, $\beta_1$, should be insignificant if the two groups are matched (or comparable).

negative for the market quality variables QSPREAD, IC, LRISK, |OIB|, RVOL and positive for DEPTH, TOP1DEPTH, TOP5DEPTH.

We expect that higher AT intensity is associated with greater depth in the market. This implies that the alternative hypothesis is:

$$H_A^1 : \beta_3 > 0$$

for MKT-QUALITY $\in$ DEPTH, TOP1DEPTH, TOP5DEPTH. The alternative hypothesis for the efficiency measures is:

$$H_A^1 : \beta_3 < 0$$

where MKT-QUALITY $\in$ (|VR$-$1|, KURTOSIS). If AT improves price efficiency, we expect |VR $-$ 1| to be closer to zero. Similarly, if AT reduces extreme price movements, we expect KURTOSIS to be close to zero.

# 6 Data

We start the analysis with a sample of 1577 securities listed on the NSE in August 2013. Out of these, we select a subset of liquid securities, such that they have an average of at least 50 trades per day, during both the *pre co-lo* and *post co-lo* periods. This reduces the sample to 918 securities. Table 1 provides the summary statistics of this sample. The average firm size was Rs.45.5 billion in the *pre co-lo* period, but the sample ranged from Rs.160 million to Rs.2.9 trillion in that period. The overall market size was lower in the *post co-lo* period, with the range of values decreasing from Rs.80 million to Rs.2.8 trillion in the *post co-lo* period, even though the average firm size was higher at Rs.62.4 billion. We also see a decline in the total turnover and number of trades in the *post co-lo* period.

The table shows that the average AT intensity went up from around 3% in the PRE CO-LO period to 18% in the POST CO-LO period. The sample standard deviation ($\sigma$) also increased from 4.58 to around 18.63, showing cross-sectional variation in AT adoption. Thus, compared to the average of 18% in 2013, the AT intensity for a single security was at a maximum at 82%. What did this do for the speed of order placement and trading on the exchange after co-location was introduced? Table 2 presents the average time taken between order modifications for the *pre co-lo* and the *post co-lo*

**Table 1** Descriptive statistics

The table presents summary statistics on average market characteristics of the sample of 918 liquid securities chosen in the first stage of the analysis. The characteristics are market capitalisation (MCap), Number of trades (Trades), Price, Turnover, Floating stock (FloatStock), and AT intensity (AT).

| | **Mean** | $\sigma$ | **Min** | **Median** | **Max** |
|---|---|---|---|---|---|
| *Pre co-lo* | | | | | |
| MCap (Rs. Billion) | 45.54 | 177.66 | 0.16 | 5.76 | 2,955.52 |
| Price (Rs.) | 228.83 | 442.77 | 4.45 | 95.55 | 7,200.63 |
| Turnover (Rs. Million) | 167.49 | 582.03 | 0.13 | 10.83 | 7,517.32 |
| Trades (Number) | 7,088.83 | 18,007.98 | 50.86 | 1,089.28 | 188,705.91 |
| FloatStock (%) | 46.99 | 17.29 | 1.12 | 46.59 | 100.00 |
| **AT** (%) | **2.96** | **4.58** | **0.00** | **0.93** | **27.78** |
| *Post co-lo* | | | | | |
| MCap (Rs. Billion) | 62.48 | 227.97 | 0.08 | 5.63 | 2,782.98 |
| Price (Rs.) | 275.52 | 729.30 | 0.16 | 78.08 | 12,115.13 |
| Turnover (Rs. Million) | 113.50 | 382.24 | 0.03 | 6.24 | 4,652.26 |
| Trades (Number) | 5,650.17 | 13,092.70 | 50.68 | 828.51 | 100,136.04 |
| FloatStock (%) | 46.92 | 17.74 | 1.12 | 45.93 | 100.00 |
| **AT** (%) | **18.18** | **18.63** | **0.00** | **11.12** | **81.78** |

periods.[16] The average time to modifications decreased by 10× for AT orders on average (from 188 to 15 seconds), while the mean time to modification for non-AT orders increased on average (from 1085 to 1404 seconds).

Such increases in AT and HFT in the financial markets raise the question of the role that AT plays as counterparty to trades. Do they "demand" liquidity from non-AT traders (i.e., are trades initiated by AT orders where an non-AT order is the counterpart) Or do they "supply" liquidity to non-AT traders (the non-AT order initiates the order with an AT order as the counterpart)? In 2009, when AT was a small fraction of the order flow, data analysis shows that AT demanded liquidity for 5.88% of the trades in the market, while AT supplied liquidity on 4.43% of the trades. In 2013, the demand had shifted to 36% of trades. On the supply side, AT orders were counterparties to 37% of the trades.

Thus, non-AT orders still constitute a significant part of orders demanding and supplying liquidity. This evidence is contrary to the perception that ATs

[16]These calculations do not include orders that did not exhibit any changes after they entered the limit order books. The changes may have been a modification of the order, a cancellation or execution. The fraction of all such non-active orders was 64.7%, which reduced to 41.22% in the post co-lo period.

**Table 2** Summary statistics about order modifications

The table shows the summary statistics of the number of modifications to an order, and the time between order modifications averaged across the sample of 918 securities, in the *pre co-lo* and *post co-lo* periods. These are presented for both AT and non-AT orders. The number of modifications have been rounded off to the nearest digit. The values of the average time for order modifications are in seconds.

| | | Mean | $\sigma$ | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| # of order modifications | | | | | | |
| *Pre co-lo* | NON-AT | 3 | 20 | 1 | 1 | 2 |
| | AT | 17 | 128 | 1 | 2 | 5 |
| *Post co-lo* | NON-AT | 7 | 75 | 1 | 1 | 2 |
| | AT | 51 | 447 | 1 | 5 | 47 |
| Time between order modifications | | | | | | |
| *Pre co-lo* | NON-AT | 1,085.4 | 2,648.4 | 50.9 | 86.7 | 613.0 |
| | AT | 187.8 | 1,120.9 | 1.7 | 3.0 | 8.9 |
| *Post co-lo* | NON-AT | 1,403.7 | 3,296.3 | 8.4 | 67.7 | 879.5 |
| | AT | 14.8 | 283.9 | 0.08 | 0.7 | 3.1 |

are mostly the liquidity consumers.

## 6.1 Matched sample of stocks

We have seen that AT adoption before and after *co-lo* varies widely across the securities in the sample (Figure 2). There is also considerable heterogeneity in the characteristics of these securities (Table 1).

In order to establish the impact of AT on market quality, we need to identify sub-samples where the change in AT intensity across the *co-lo* event is homogeneous within a group. Next, in order to control for the possible endogeniety bias, we need to identify securities within each group that are matched in all ways other than the AT intensity.

Figure 4 is the density plot of the change in the AT intensity for the sample between the *pre co-lo* and *post co-lo* periods. Those securities where the AT intensity changes by a value greater than the $70^{th}$ percentile point is considered to have high AT adoption. These are the candidates for the "treatment group". Those securities where the change is less than the $30^{th}$ percentile point become the candidates for the "control group" with low AT adoption. The change in AT intensity for the treatment group securities is 16.50% on average, which is statistically higher than the average of the control group at 5.39%. There are 276 securities in each group.

**Figure 4** Density of the difference in AT intensity before and after *co-lo*

The graph shows the density of the difference in AT intensity between the *pre co-lo* and *post co-lo* periods for the full sample of 918 securities.
The two shaded areas present the areas where the change in AT intensity is either greater than 16.50% ($70^{th}$ percentile) or less than 5.39% ($30^{th}$ percentile).

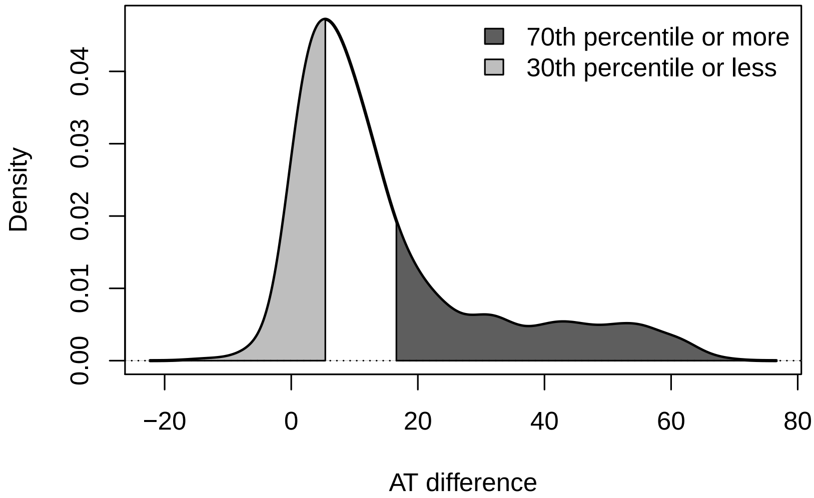


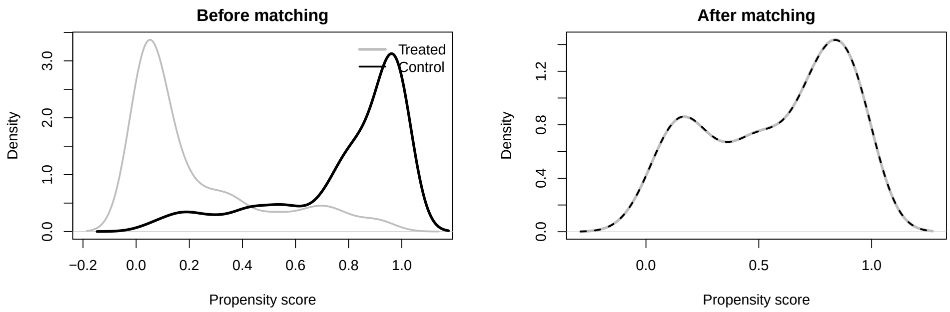

**Table 3** Mean tests of match covariates, before and after matching

The table presents the match balance statistics of the covariates of the set of securities that are the candidates for the treatment and control sample. The first three columns show tests of difference in the sample mean before matching, while the next three show these tests for the subset selected after matching.
The match balance is demonstrated using both the standard t-test and the Kolmogorov-Smirnov (KS) test.

| Covariate | Before matching | | | After matching | | |
|---|---|---|---|---|---|---|
| | t-stat | p-value | | t-stat | p-value | |
| | | t | KS | | t | KS |
| MCap | 22.83 | 0.00 | 0.00 | -0.47 | 0.64 | 0.84 |
| Price | 17.26 | 0.00 | 0.00 | -0.64 | 0.52 | 0.32 |
| Turnover | 16.73 | 0.00 | 0.00 | -0.43 | 0.67 | 0.08 |
| Trades | 13.58 | 0.00 | 0.00 | -0.10 | 0.92 | 0.26 |
| Floating stock | -1.69 | 0.09 | 0.14 | 0.55 | 0.59 | 0.50 |
| AT-intensity | 10.62 | 0.00 | 0.00 | -1.83 | 0.07 | 0.14 |

**Figure 5** Density of the propensity score, before and after matching

The first graph shows the density plot of the propensity score of the set of 279 securities that are candidates for the treatment and the control groups (before matching).
The second graph shows the density of the propensity score of the set of securities selected from both groups after matching.




For each security with a change in AT intensity greater than the 70th percentile value, we locate one where the change in AT intensity is less than the 30th percentile value. Matching is done by calculating a propensity score with a set of firm characteristics as covariates. The covariates include size (market capitalisation), price, floating stock, traded volume, and number of trades. Table 3 shows the match balance statistics of the two sets, before and after matching. After matching, a balance is achieved for all the covariates in the pre co-lo period.

Figure 5 plots the empirical distributions of the propensity score of the two groups, before and after matching, in the *pre co-lo* period. The overlap between the density of the two sets before matching indicates the region of common support, which becomes a tight overlap after matching.

The final matched set contains 91 securities in the treatment group (high AT adoption) and 73 in the control group (low AT adoption).

## 6.2 Matched sample of dates

The previous matching exercise does not correct for broad market-wide and economy-wide differences in the periods before and after *co-lo*. For this, we match specific dates in these two periods for similar levels of Nifty volatility. Table 4 presents the balance statistics for the matched dates from each period. The difference in the Nifty volatility for the matched dates from the two periods is insignificant by both the standard t-test and the Kolmogorov-

**Table 4** Mean test of market volatility, before and after matching dates

The table presents the match balance statistics for market index realised volatility between the treated and the control set of dates after matching. '*Treatment*' refers to the dates in pre co-lo period, while '*Control*' dates are the dates in the post co-lo period. After matching, we get 59 dates in each set.

| | Before Matching | After Matching |
|---|---|---|
| Mean (Treatment) | 14.92 | 12.35 |
| Mean (Control) | 9.33 | 12.34 |
| T-test p-value | 0.00 | 0.41 |
| Kolmogorov-Smirnov p-value | 0.00 | 1.00 |
| Number of days (Treatment) | 291 | 59 |
| Number of days (Control) | 260 | 59 |

Smirnov statistic.[17]

The matching procedure locates 59 matched dates in each period. The final sample comprises the 91 treatment group securities, compared with 73 control group securities, both observed on these matched 59 dates before and 59 dates after *co-lo*.

# 7 Results

We use the sample, matched for endogeniety bias and macro-economic bias, as inputs in the DID regression described in Section 5.4. The estimation is run for all the market quality variables described in Section 4.2 calculated at five-minute intervals, where the variables are winsorised.[18] $\hat{\beta}_3$ for each of the DID regressions is presented in Table 5.

## 7.1 The impact of AT on market quality

We first discuss the impact of AT on the liquiidty of the treated versus the control securities. The value of the coefficient, $\hat{\beta}_3$, in Table 5 for both

[17]The advantage of the Kolmogorov-Smirnov test as opposed to the standard t-test is that it tests for the significant differences across the entire distribution rather than just the averages

[18]The winsorisation is done as follows: values smaller than the 0.05% quantile are set equal to the value of that quantile, and values larger than the 99.95% quantile are set equal to the respective quantile.

**Table 5** DID $\hat{\beta}_3$ for all market quality measures

The table presents estimates for the following DID regression with controls:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1\text{AT}_i + \beta_2\text{CO-LO}_t + \beta_3\text{AT}_i \times \text{CO-LO} + \\ &\quad \beta_4\text{NIFTY-VOL}_t + \beta_5\text{INTRADAY-DUMMY}_t + \beta_6\text{LTP}_{i,t} + \epsilon_{i,t}\end{aligned}$$

where $i$ = 1,...,N indexes firms, $t$ = 1,...,T, indexes 5-minute time intervals. MKT-QUALITY$_{i,t}$ is one of the market quality variables: transactions costs (QSPREAD, IC), depth (TOP1DEPTH, TOP5DEPTH, DEPTH, |OIB|, market risk (LRISK, RVOL, RANGE), efficiency (|VR-1|, and extreme price movements KURTOSIS) for security $i$ at $t$. Logarithmic values of the depth measures (DEPTH, TOP1DEPTH, TOP5DEPTH) are used.
AT$_i$ is a dummy that takes value 1 for *treated* securities and 0 otherwise. CO-LO is a dummy that takes value 1 for observations belonging to the post co-lo period and 0 otherwise. AT×CO-LO is an interaction term that captures the effect of the treatment. NIFTY-VOL$_t$, INTRADAY-DUMMY$_t$ and LTP$_{i,t}$ are the control variables. NIFTY-VOL controls for market volatility, INTRADAY-DUMMY controls for intraday effects in the market quality variables, and LTP$_{i,t}$ controls for the security prices in the interval.
For brevity, we present only $\hat{\beta}_3$, which is the coefficient of interest. Standard errors are heteroscedasticity consistent, clustered at the firm level.

| **Mkt-Quality** | $\hat{\beta}_3$ | Std. Error | t value | Pr(> \|$t$\|) | $R^2$ | # of Obs. |
|---|---|---|---|---|---|---|
| QSPREAD | -0.35 | 0.05 | -6.82 | 0.00 | 0.14 | 1,094,827 |
| IC | -0.79 | 0.10 | -7.95 | 0.00 | 0.19 | 1,092,347 |
| | | | | | | |
| \|OIB\| | -13.87 | 3.98 | -3.49 | 0.00 | 0.08 | 1,094,827 |
| DEPTH | 0.33 | 0.15 | 2.22 | 0.03 | 0.20 | 1,094,827 |
| TOP1DEPTH | 0.16 | 0.17 | 0.95 | 0.34 | 0.09 | 1,094,827 |
| TOP5DEPTH | 0.33 | 0.15 | 2.19 | 0.03 | 0.10 | 1,093,177 |
| | | | | | | |
| \|VR-1\| | -0.03 | 0.01 | -3.13 | 0.00 | 0.01 | 18,067 |
| KURTOSIS | 2.76 | 2.48 | 1.12 | 0.26 | 0.14 | 873,946 |
| | | | | | | |
| RVOL | -2.65 | 0.71 | -3.76 | 0.00 | 0.05 | 1,094,673 |
| RANGE | -16.90 | 6.84 | -2.47 | 0.01 | 0.00 | 1,094,827 |
| LRISK | -0.02 | 0.00 | -4.75 | 0.00 | 0.04 | 1,092,111 |

QSPREAD and IC is negative and significant. QSPREAD of the treated securities reduced by an estimated 35 basis points (bps) as a result of higher AT activity in the *post co-lo* period in comparison to the control stocks. Similarly, IC for the treated securities reduced by 80 bps. This implies higher levels of AT causes a significant *reduction* in the transactions costs. These results are consistent with most of the literature (Hendershott *et al.*, 2011; Hasbrouck and Saar, 2013) which find that AT improves the liquidity of the markets.

The coefficient, $\beta_3$, for |OIB| is negative and significant. The order imbalance reduced by 14% for treated securities compared to the control. The coefficient on DEPTH is significant and positive, as is the depth at the best five bid and ask prices. This indicates that higher levels of AT increases the number of shares available for trade in the market. However, the results do not hold for the depth at the best bid and ask price. The estimated coefficient is positive but insignificant, suggesting that AT has no impact on the depth at the best prices.[19]

Overall, we infer that AT either has a positive impact on liquidity in terms of a reduction in liquidity costs, but not necessarily an impact on the depth of the markets.

We next discuss the volatility measures. The results on the price risk measures are in line with the findings of the previous literature. $\hat{\beta}_3$ on both the price risk measures (RVOL, RANGE) is negative and significant. This implies that RVOL *decreased* by 2.65% for the treated securities. The decrease in RANGE is even more substantial. Both of these show that higher AT leads to lower price volatility.

Chordia *et al.* (2013) raise an important concern regarding the effect of AT on the liquidity of the markets. They argue that it is not just the level of the liquidity that matters, but also the *variability* of the liquidity (which becomes even more important around stress periods) that matters. Table 5 reports the $\hat{\beta}_3$ coefficient for liquidity risk, LRISK, as negative and significant. This indicates that higher levels of AT is not associated higher intraday variability of liquidity. This runs counter to public and regulatory perception about market liquidity being transitory as a consequence of higher AT intensity.

We next proceed to analyse the impact of AT on price efficiency. The estimated $\hat{\beta}_3$ is negative and significant for |VR-1|, showing securities with higher

[19] The evidence on the impact of AT on depth in the literature is mixed. For example, Hendershott *et al.* (2011) find that quoted depth reduced after automation, HASBROUCK-SAAR2013 find an improvement in the depth as a result of high frequency trading.

AT experience a movement towards a random walk process as opposed to the securities with lower AT. This indicates lesser persistence in intraday high-frequency returns, implying higher price efficiency intraday as a consequence of higher AT.

## 7.2 Does AT result in a higher incidence of 'flash crashes'?

In Table 5, the KURTOSIS coefficient estimate is insignificant. However, the sign of the coefficient is positive, which implies a higher probability of extreme price movements intraday due to AT, if securities returns are normally distributed. Since extreme price movements have been a matter of significant concern amongst the regulators worldwide, we design an alternative approach using the matched sample to further test the incidence of extreme intraday price movements due to AT.

For every security, $i$, we test the frequency of price movements greater than a threshold price relative to the last trading price. For our data, we carry out the analysis for three threshold values: 2%, 5%, and 10%. We calculate a binary variable, $\text{BREACHES}_i$, which takes value 1 for movements beyond the threshold range and 0 otherwise. These are aggregated within each five-minute interval as an extreme price movement measure. For example, if $\text{BREACHES}_i = 5$ with a total of 20 trades in a five-minute interval, the value of the extreme-price movement measure will be $5 \times 100/20 = 25\%$.

We calculate this measure for each security $i$ in the matched sample at three threshold values to calculate three extreme price movement measures called EXTREME@2 (for price breaches in extreme of 2%), EXTREME@5, and EXTREME@10. We then estimate a DID regression to test if there is a higher incidence of extreme price movements as follows:

$$\begin{aligned}\text{EXTREME@N}_{i,t} \;=\; & \alpha + \beta_1 \text{AT}_i + \beta_2 \text{CO-LO}_t + \beta_3 \text{AT}_i \times \text{CO-LO}_t + \\ & \beta_4 \text{NIFTY-VOL}_t + \beta_5 \text{INTRADAY-DUMMY}_t + \text{LTP}_{i,t} + \epsilon_{i,t}\end{aligned}$$

where $N = 2, 5, 10$.

Table 6 reports the estimates of $\hat{\beta}_3$ for the above regression. The table shows that for price movements exceeding 2% and 10% as the threshold, the coefficient of $\beta_3$ is not significantly different from zero.[20] This indicates that the incidence of the occurrence of price movements beyond 2% and 10% for

[20]The table reports the F-stat p-value, which tests for the joint significance of all explanatory variables of the model. All p-values are less than 0.05, indicating the significance of the model. The $R^2$ values for these model specification lies in the range of 0-3%.

**Table 6** DID $\hat{\beta}_3$ for extreme price movement measures

The table presents the estimation results for the DID regression:

$$\begin{aligned}\text{MKT-QUALITY}_{i,t} &= \alpha + \beta_1 \text{AT}_i + \beta_2 \text{CO-LO}_t + \beta_3 \text{AT}_i \times \text{CO-LO}_t + \\ &\quad \beta_4 \text{NIFTY-VOL}_t + \beta_5 \text{INTRADAY-DUMMY}_t + \text{LTP}_{i,t} + \epsilon_{i,t}\end{aligned}$$

with price movements measures of EXTREME@2, EXTREME@5 and EXTREME@10 as the market quality variables.

| **Mkt-Quality** | $\hat{\beta}_3$ | Std. Error | t value | Pr(> $\lvert t \rvert$) | F-stat p value | Num. of Obs. |
|---|---|---|---|---|---|---|
| EXTREME@2 | -1.60 | 1.63 | -0.98 | 0.33 | 0.00 | 739,240 |
| EXTREME@5 | -2.39 | 0.90 | -2.65 | 0.01 | 0.00 | 739,240 |
| EXTREME@10 | -0.05 | 0.05 | -1.07 | 0.28 | 0.00 | 739,240 |

the treated securities is the same that for the control securities. For price movements in excess of 5%, the coefficient value is significant and negative. These suggests that there is either a *reduction* in extreme price movements for securities with higher AT or that they are the same as that for securities with low AT. In summary, the results suggest that higher AT does not result in a higher incidence of 'flash crashes'.

# 8 Robustness tests

The research design attempts to adjust for endogeniety bias by analysing only those securities that are similar in factors that could simultaneously be the underlying causes of change in AT activity and market quality. However, there can be other factors that are overlooked or logical flaws in the research design used that drive the results obtained. The following tests seek to address possible threats to validity of the results:

1. Simulating a placebo
2. Testing sensitivity to match design

## 8.1 Simulating a placebo

We simulate a placebo to test the robustness of the results. The placebo in this case is a treatment group that is known to be unaffected by the intervention. In our case, since the intervention is the increase of AT activity,

**Table 7** Testing the null of no change due to AT in a placebo

The table presents the regression results using simulated placebo tests that are run 1000 times. In each run, 91 securities are randomly picked from the control group as the treatment group and are matched against the remaining control group securities.
The values in column 2 report the fraction of times the null of $\hat{\beta}_3 = 0$ is rejected at a 5% level of significance.

| **Mkt-Quality** | Number of rejections of $\hat{\beta}_3 = 0$ (in %) |
|---|---|
| QSPREAD | 1.7 |
| IC | 3.2 |
| | |
| \|OIB\| | 4.4 |
| DEPTH | 5.3 |
| TOP1DEPTH | 4.2 |
| TOP5DEPTH | 4.0 |
| | |
| \|VR-1\| | 3.7 |
| KURTOSIS | 3.6 |
| | |
| RVOL | 0.3 |
| RANGE | 4.6 |
| LRISK | 3.5 |

a possible placebo is the set of securities known to have low levels of AT activity. In a comparison of such a treatment group and control group where both have low AT activity, the DID estimate should not be different from zero.

In our case, we generate a dataset with a randomly selected set of 91 from the 276 candidates for the control group set in Section 6.1 and matched against the remaining 185 securities, using the same set of covariates described in Section 5.2. We repeat this exercise 1000 times, and we test the number of times the null of $\hat{\beta}_3 = 0$ is rejected.

Table 7 reports the percentage of times the null of $\hat{\beta}_3 = 0$ is rejected. For all the measures, we see that the null is rejected less than 5% of the time. This indicates that there is no impact on market quality in the absence of changes in AT intensity, which is consistent with the results in Section 7.

**Table 8** DID $\hat{\beta}_3$ with different set of covariates in matching

The table reports the $\hat{\beta}_3$ for the DID regression re-estimates by dropping one of the original matching covariates one at a time.
'+', '**', '*' indicate significance at the 1%, 5% and 10% levels, respectively.

| **Mkt-Quality** | **Dropped covariate** Floating stock | Market cap | # of trades | Price | Turnover |
|---|---|---|---|---|---|
| QSPREAD | $-0.35^{+}$ | $-0.59^{+}$ | $-0.36^{+}$ | $-0.30^{+}$ | $-0.36^{+}$ |
| IC | $-0.78^{+}$ | $-1.12^{+}$ | $-0.89^{+}$ | $-0.73^{+}$ | $-0.81^{+}$ |
| \|OIB\| | $-16.10^{+}$ | $-9.99^{+}$ | $-17.87^{+}$ | $-17.69^{+}$ | $-15.11^{+}$ |
| DEPTH | $0.31^{**}$ | $0.25^{*}$ | 0.16 | 0.10 | $0.33^{**}$ |
| TOP1DEPTH | 0.05 | 0.01 | 0.13 | -0.07 | 0.06 |
| TOP5DEPTH | 0.24 | 0.21 | $0.31^{**}$ | 0.08 | $0.27^{*}$ |
| \|VR-1\| | $-0.03^{+}$ | -0.03 | -0.01 | -0.03 | -0.03 |
| KURTOSIS | $6.26^{+}$ | $5.02^{**}$ | $7.66^{+}$ | $8.90^{+}$ | $6.58^{+}$ |
| RVOL | $-2.52^{+}$ | $-5.57^{**}$ | $-2.46^{+}$ | $-2.19^{+}$ | $-2.68^{+}$ |
| RANGE | $-18.19^{+}$ | $-24.00^{+}$ | $-26.62^{+}$ | $-15.03^{**}$ | $-22.36^{+}$ |
| LRISK | $-0.02^{+}$ | $-0.02^{+}$ | $-0.02^{+}$ | $-0.01^{+}$ | $-0.02^{+}$ |

## 8.2 Testing sensitivity to match design

Another test of the robustness is re-estimation with variations in the the matching design. Here, the matching framework is modified by dropping a co-variate at a time, using the modified set of matching covariates to obtain a new dataset of treatment and control group securities and re-estimating the DID regression with this new sample. Table 8 reports the results of the re-estimated $\beta_3$ coefficients from the DID regressions using these modified datasets. The regression estimates with the dropped covariates are qualitatively similar to the ones reported with all the covariates in Table 5. There is some variation in the magnitude of the coefficient for most, but the direction of the impact of AT on market quality remains the same.

The results on DEPTH and TOP5DEPTH and KURTOSIS do change, suggesting that these results are vulnerable to the match design and require further work to establish causality.

# 9 Conclusion

Over the last three decades, financial markets have seen tremendous developments with the use of technology. One such development is the use of algorithms to place orders for trade execution on electronic exchanges. While this was considered beneficial to investors to achieve best trade execution initially, today, algorithmic trading is being targeted by regulators for harming investor interests.

A growing base of research analyses the effect of AT on the quality of market outcomes. However, establishing causality remains an issue. One reason for this is a lack of identification of which trade is AT. Another reason is an endogeniety bias because both higher AT and better market outcomes could be driven by common unobserved factors.

The advantage of this paper is a unique data set with clear identification, allowing for a research design to overcome the endogeniety bias. The analysis uses a change in technology when the National Stock Exchange introduced co-location services during this time period, which caused an increase in AT intensity. The design also identifies pairs of securities that are matched by firm characteristics but have different levels of AT activity. The underlying assumption is that if there is a difference in the market quality after co-location, which is different for the security with high AT compared to the security with low AT, the change can be attributed to AT.

The research design identifies 91 pairs of securities, and 59 days before and after co-location, after the matching procedure. A difference-in-difference regression is estimated, with controls for intraday volatility dynamics. The results suggest that AT improves market quality. There are improvements in transactions costs, volatility, and buy-sell imbalance. There are improvement in some, but not all of the depth measures, and these are sensitive to the match design.

Two areas where the results provide new insights are the intraday volatility of liquidity and the probability of extreme price movements and reversal over a very small period during the day, often referred to as a *flash crash*. Policy makers have been very concerned that liquidity provided by AT can rapidly deteriorate when news breaks. Our results show that the liquidity risk is *lower* with more AT. A similar concern has often been voiced about the probability of a *flash crash*. However, we find that higher AT intensity either leads to *fewer* of such episodes or has no effect.

This work highlights several questions that can be answered with data that allow for a precise and fine measurement of both AT and market quality. For example, what drives the cross-sectional variation in AT intensity across securities? Are differences in high AT activity across securities temporary, driven by the momentary arrival of news and information, or are these more structural, driven by differences in firm characteristics? Our results indicate that there are more benefits than costs to securities that attract higher AT activity. With proper safeguards in place, more meaningful policy measures could be built to increase the level of AT trading to a broader base of securities, rather than inhibit it.

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