Man vs. Machine:
Liquidity Provision and Market Fragility

by

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Abstract

We empirically investigate the *reliability* and the *consistency* with which algorithmic and human traders provide liquidity in electronic order-matching markets, and the consequent regulatory implications for the fragility in available liquidity in these markets. We find strong evidence that in turbulent periods, in contrast to manual traders, algorithmic public traders significantly reduce their participation and liquidity provision in trades, significantly reduce the extent to which they post new liquidity-supplying limit orders; and significantly reduce the aggressiveness of these limit orders, effectively increasing the price at which they are willing to supply liquidity. This greater withdrawal of algorithmic traders is directly associated with the disappearance of the speed based information advantages of algorithmic traders in the complexity of turbulent periods. We find that this has a significant propensity to generate feedback loops, and induce "contagion" through withdrawals in liquidity provision in related stocks, potentially making markets more "fragile". Our results suggest that, in contrast to manual traders adapting in (higher latency) real time, algorithmic trade execution appears less conducive to low impact adjustment of complex information asymmetries or flows. Overall, our results reinforce regulatory concerns about the potential for systemic fragility in this context.

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1. Background and Motivation

Equity markets are now largely organized as electronic order matching markets, and their liquidity arises from the standing buy and sell limit orders posted, *entirely voluntarily,* by traders with no formal affirmative obligations to maintain liquid and orderly markets.[1] Traders supply liquidity (to earn rather than pay the bid-offer spread) only when it is optimal for them to do so as part of their trading activities. In the context of such markets, an important area of concern for exchanges, regulators, and market participants, is the consistent and continual availability of limit orders to execute against – in good times and bad – so that liquidity demanders can reliably get immediate execution of their orders. This concern has been significantly heightened following the rapid growth in algorithmic traders (hereafter "AT"), who harvest bid-offer spreads without any human trade-by-trade intervention through computer-based automated trading decisions and executions, often without pre-meditated directional bets, participating on both sides of the book, turning over inventory intraday with minimal capital investment as often as is optimal.[2] In this context, this paper empirically investigates the participation and transactional liquidity provided by AT – the "machine" – and human traders – the "man" (hereafter "MT") – during periods of market turbulence or stress, relative to what they do in "normal" periods, and the resultant implications for the quality and fragility of markets.

Periods of market stress and turbulence are clearly characterized by significantly high levels of information intensity, or information-related asymmetry or uncertainty. AT should

[1] In contrast, the traditional "market-maker" of the early nineties – like the NYSE specialist, or the competing market maker on NASDAQ or the London Stock Exchange – had affirmative obligations to always stand ready to supply liquidity and maintain orderly markets.
[2] Reports of the Tabb Group consistently estimate that high frequency traders alone – a subset of AT – now execute well over half of the U.S. equity trading volume.

arguably have a competitive speed advantage over MT during such periods, since they can access and process data faster through their framework of pre-programmed artificial intelligence and algorithms without being constrained by limits to human cognition and bounds of human rationality in accessing and processing data across multiple sources (Biais and Wooley, 2011). This should lead to MT facing adverse selection costs relative to AT (Biais, Foucault, and Moinas, 2010). Consistent with an AT informational advantage, Brogaard (2010) and Hendershott and Riordan (2010) find that AT lead with respect to price discovery, and impound more information that human orders. However, theirs and other extant empirical analyses only span "normal" periods. If AT also enjoy a competitive advantage over MT in turbulent times as well, then it is the manual rather than the algorithmic voluntary liquidity suppliers that should be withdrawing from the market in those turbulent times.

There are at least two important reasons why AT may reduce their participation and liquidity supply in turbulent markets relative to MT. First, we argue that algorithms pre-programmed ex ante cannot deal with the complexity of turbulent periods as effectively as manual traders. "Data" or hard news releases are not necessarily the same as "information" – they have to be processed into usable information. The processing can be simple: e.g., comparison with prices of related assets and exploiting any arbitrage or quasi-arbitrage opportunities; or observing the prices across fragmented markets and trading accordingly. In such simple cases, AT have a clear advantage over MT. However, processing of potentially unrelated and unusual data or news clips into economically relevant price information can often be too complex for pre-programmed algorithms. Zigrand, Shin and Beunza (2011) state this eloquently: "*... algorithms know the price of everything and the value of nothing.*" This can be for several reasons. One, it is imperfect, subjectively interpreted through prisms of assumptions and priors, and extremely challenging across multiple dimensions (see, for example, Mehta, Neukirchen, Pfetsch, and Poppensieker, 2012). Because of this, traders face "preference uncertainty", modeled in the specific context of optimal trading strategies and equilibrium prices in the presence of liquidity shocks – a context directly relevant to this paper – by Biais, Hombert, and Weill (2014). It is seriously questionable, whether artificial intelligence can be pre-programmed effectively into algorithms to comprehensively cover the totality of outcomes that can address the entire feasible spectrum of preference uncertainties and economic complexities.[3] Two, this challenge is made even more difficult by the fact that the rapid speed of trading – which is what enables HFTs to exploit price distortions before slow traders can – also limits the time available for information processing: Dugast and Foucault (2014) theorize that such constrained information processing would increase the incidence of 'mini-flash crashes' – large, sudden price drops or spikes that are immediately followed by an equally quick recovery – as in the 'twitter crash' of April, 2013.[4] Three, periods of market stress are rare and unique, arguably posing severe challenges to algorithms whose decisions are based on pre-programmed routines whose parameters are set ex ante. The ever increasing presence and constantly changing role of other algorithms in the system require algorithms to adapt continually and further reduces the benefits of applying rules based on lessons learnt from the past. Risks of serious glitches while running new or adapting old algorithms are high even in normal times.[5] Consequently, AT might focus on "*building systems that deal with the worst-case scenarios, where blunt, one-size-fits-all tools suffice to shut down activity and to ensure the trader can exit the market as quickly as possible*"

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[3] Algorithms in use in financial markets do not appear to be overly complex (Cliff, Brown, and Treleaven, 2012). This is further reinforced by Zigrand, Shin, and Buenza (2011): "*Most computer algorithms seem at the moment to largely consist of relatively short (and therefore simple) computer code. It seems that the inputs into the algorithm largely consist of the past behaviour and data series of this very asset itself, and perhaps of some related securities, mechanical news tags as well as engineering state variables such as the state of latency in the network, the temperature in the data center,….and the like*"

[4] The Dow Jones dropped more than 150 points on a false tweet that the White House was attacked, but recovered within two minutes when the tweet was recognized as being errorneous.

[5] For example, in August 2012, Knight Capital, then a 17-year-old market-making firm doing $20 billion in trades a day on the NYSE, lost $440 million, four times its net annual income, in 30 minutes, while running a new computer program.

(Yadav, 2014). In other words, in turbulent, unpredictable conditions, AT might minimize their losses by simply applying the "kill switch". The evidence in Buenza et al (2011) supports the widespread use of kill switches in selected periods. In the same vein, Zigrand, Cliff and Hendershott (2011) also argue that ATs reliance on automated risk management algorithms tends to limit participation and liquidity provision during periods of market stress.

A corollary of the complexity argument is that AT should lose their informational advantage over MT during extreme events/periods of market stress.[6] However, proper scientific evidence in this regard is limited and inconclusive. Das, Hanson, Kephart, & Tesauro (2001), in the spirit of Smith (1962) – who explored continuous double auction markets with human trader subjects under experimental laboratory-style conditions, and received the Nobel Prize in Economics in 2002 for this work – pitted human traders against robot software agents, and found that the robots dominated the humans. However, the results appear to have been reversed in more recent experiments under "more realistic" conditions (De Luca, Szostek, Cartlidge, and Cliff (2011)).

A second reason why AT may reduce their participation and liquidity supply in turbulent markets relative to MT arises because AT liquidity supply activity is characterized by very limited commitment of capital and ultra-short intraday horizons, in contradistinction to traditional equity specialists and market-makers, who typically had deep pockets and inventory half-lives spanning days, not minutes. AT are the prototypical 'short-horizon' traders in De Long, Shleifer, Summers and Waldmann (1990) who bear position risks only when they expect to profitably offload their positions within their trading horizon. The AT trading advantage stems from their ability to trade in and out of positions faster than others (Javanovic and Menkveld, 2010). Such agility is hindered when capital is locked-up in a

[6] The view is captured by anecdotal comments like the following: "*Humans are likely to be best at reacting to freak situations and unexpected market shocks. […]. When the winds of change hit the market, humans are still more adaptable, flexible and able to change with the times. While algorithms can be reprogrammed, they can't be reprogrammed fast enough to take advantage of a contemporaneous shock.*" (Webb and Webb, 2014).

single position. Therefore, the lower the chances of profitable inventory rebalancing in a short period of time, which will be the case in a one-sided "extreme" market, the greater the reluctance to take a position and, conditional on participation, the smaller the position undertaken. Furthermore, AT's over-arching imperative of keeping their capital commitment low means that they are much more likely to frequently trade out of positions in turbulent markets by demanding liquidity rather than continuing to function as liquidity suppliers.

The reduction in participation and liquidity supply by AT in turbulent markets relative to MT can be exacerbated by the fact that AT is significantly more correlated than MT. Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) argue that "*there is potential for higher correlation in computers' trading actions than those in humans, since computers need to be pre-programmed and may react similarly to a given signal*"; and provide evidence "*.... that is consistent with the actions and strategies of algorithmic traders being less diverse, and more correlated, than those of non-algorithmic traders.*"[7] They find that the excess correlation does not degrade market quality on average: however, they emphasize that they have not examined extreme periods, and the behavior in those extreme periods could well be different. The complexity and short horizon arguments articulated above suggest that the behavior in normal and extreme periods should arguably be different, because ATs could consider kill switches in the extreme periods, and the simultaneous application of kill switches in turbulent periods, across traders and even across stocks, could arguably lead to a severe deterioration in liquidity. In a stress situation, many algorithms can quickly coordinate and act simultaneously and feed each other, potentially giving rise to feedback loops that make markets fragile.[8] The official CFTC/SEC report on the "Flash Crash" events of May 6, 2010 also discusses the

[7] Laube and Malcenieks (2013) also find that high frequency trading increases the commonality in both returns and in liquidity for European equities.
[8] To quote Zigrand, Shin, and Buenza (2011): "*A driver for future risk and catastrophes lies in the fact that the seemingly large bio-diversity of traders may be illusory and that in a stress situation many algorithms quickly and unwittingly coordinate, act in unison and feed on each other in a feedback loop, thereby leading to a disproportionate value destruction.*"

destabilizing feedback effect of “hot-potato” or “pass-the-parcel” behavior generated by the holding of small positions for short periods: the large volume of trading among algorithms triggered other algorithms that sold aggressively in high volume markets.[9] Zigrand, Cliff, and Hendershott (2011) argue that such feedback loops are the underlying force behind most of the financial crises, and those loops are more likely to arise, or at least may be harder to supervise, in AT environments.

Clearly, it is not surprising to see extensive concerns articulated by regulators and policymakers that, while AT improves overall liquidity, it also generates greater dangers of periodic episodic illiquidity.[10] The issue has been brought into sharper focus by the Flash Crash of May 6, 2010, and the regular occurrence of mini-crashes.[11] In September 2010, speaking before the Security Traders Association, Mary Schapiro, then Chairman of the Securities and Exchange Commission, said, “*Given their volume and access, high frequency trading firms have a tremendous capacity to affect the stability and integrity of the equity markets. Currently, however, [they]…. are subject to very little in the way of obligations either to protect that stability…. in tough times, or to refrain from exacerbating price volatility…. An out-of-control algorithm…. can also cause severe trading disruptions that harm market stability and shake investor confidence.*” In July 2011, a report by the International Organization of Securities Commissions (IOSCO), an international body of securities regulators, concluded that algorithms were "*…. clearly a contributing factor in the flash crash event of May 6, 2010.*” Other regulators have also questioned the stability of the liquidity provided algorithmically.[12] Consequently, regulatory proposals have often

[9] CFTC & SEC (2010): Findings regarding the market events of May 6, 2010.
[10] See, for example, *Foresight: The Future of Computer Trading in Financial Markets (2012) Final Project Report,* The UK Government Office for Science, London, page 11: Executive Summary.
[11] See Sornette and Becke (2011), page 13 for examples.
[12] For example, Andrew Haldane, Executive Director for Financial Stability at the Bank of England, in his speech ‘Race to Zero’ (July, 2011), said: “*Far from solving the liquidity problem in situations of stress, high-frequency trading firms appear to have added to it. And far from mitigating market stress, high-frequency trading appears to have amplified it. High-frequency trader liquidity, evident in sharply lower peacetime bid-ask spreads, may be illusory. In wartime, it disappears. This disappearing act, and the resulting liquidity void,*

endeavored to impose affirmative obligations to mandate AT to 'make' markets even during periods of stress.[13] Regulatory concerns are also highlighted by proposals aimed at constraining AT through transaction taxes, fees for and limitations on order cancellations, and other rules. [14]

In spite of the extensive regulatory concerns, and the two important reasons – complexity and AT short horizons – that could precipitate swift withdrawal of participation and liquidity supply from AT in turbulent periods, and consequent market fragility, extant empirical research has focused only on "normal" market conditions.[15] In contrast, the contribution of this paper is to focus on periods of market turbulence and stress, where stress is measured by high and persistent volatility, and/or high and persistent order imbalances, and/or high and persistent bid-ask spreads. We empirically test whether AT participation in trades and the contribution of AT to transactional liquidity supply – i.e., posting of standing buy and sell limit orders that have provided trade execution and immediacy to other traders – is as reliable and stable as that of MT even in times of market stress; or whether the core reasons we have discussed – complexity and AT short horizons – results in AT being just the "fair weather" liquidity suppliers they are feared by regulators to be.

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is widely believed to have amplified the price discontinuities evident during the Flash Crash. High-frequency trader liquidity proved fickle under stress, as flood turned to drought".

[13] For example, the European Commission's Markets in Financial Instruments Directive (MiFID II) along with a related regulation (MiFIR), proposed affirmative obligations requiring AT to *"be in continuous operation during the trading hours"* and also that *"the trading parameters or limits of an electronic trading strategy shall ensure that the strategy posts firm quotes at competitive prices with the result of providing liquidity on a regular and ongoing basis to these trading venues at all times, regardless of prevailing market conditions."*

[14] For example, House Resolution 1068 sought to impose a trading tax of .25%, and the European Commission had proposed a trading tax of 0.1% on shares and bonds, and 0.01% on derivatives. Other proposals include fees when the number of orders cancelled by a trader exceeds a certain level; or a requirement for quotes to have a minimum life before they can be canceled or revised.

[15] Hendershott and Riordan (2013) find that high frequency traders play a positive role in price efficiency through their marketable orders. Hasbrouk and Saar (2011) find that low-latency activity improves traditional market quality measures such as short-term volatility, spreads, and displayed depth in the limit order book. Brogaard (2010) also finds that high-frequency traders provide liquidity and correct mispricing of securities. Hendershott, Jones, and Menkveld (2011) find that the introduction of auto-quote on the NYSE improves liquidity and enhances the informativeness of quotes. Raman, Robe and Yadav (2014) find that electronic market makers in the U.S. energy futures markets withdraw from trading against customer order flow in stressful periods, while the erstwhile locals in the futures pits increased their trading against customer order flow in such periods; and they attribute this to the reputational concerns created by the absence of anonymity while trading face-to-face in the pits.

The empirical analyses in this paper are based on trades and orders data from the National Stock Exchange of India ("NSE"). NSE data are particularly suitable for this study because the NSE has always been an electronic order matching market with all liquidity suppliers always entirely voluntary, and algorithmic execution was permitted only after a clearly specified date in 2008 – we exploit this feature by comparing trading before and after algorithmic trading. In contrast, the U.S. equity markets were at least partially dealer markets with affirmatively obliged market makers, and not always purely electronic without any trading floor, which makes it difficult to isolate the specific contribution of the algorithmic nature of voluntary liquidity supply to any observed potential for fragility. Further, our data also provides broad trader classifications and flags algorithmic trades within each classification; thereby, enabling benchmarking algorithmic traders with other manual, voluntary traders of the same trader type. Such a benchmarking provides a cleaner estimate of the effect of automation on trading strategies. Therefore, the NSE provides an excellent laboratory to investigate the impact of AT on market fragility. Our results are based on comparing two periods across different categories of traders: May 2006, during which there were no AT – only MT, and May 2012, during which there were both AT and MT.

We document results of considerable academic and regulatory importance. First, we find strong evidence that, in contrast to manual traders, algorithmic traders reduce their participation and their transactional liquidity provision in periods of significantly high and persistent volatility, significantly high and persistent customer order imbalances, and significantly high and persistent bid ask spreads. There are several aspects of this result that are noteworthy: (a) the reduction in transactional liquidity provision is accompanied also by a massive reduction in the placement of new orders by all categories of algorithmic traders (relative to the manual traders in each of those categories); (b) the reduction in transactional liquidity provision is also accompanied by a decrease in the aggressiveness of all algorithmically posted orders (relative to the corresponding aggressiveness of manually posted orders), except for algorithmic orders of exchange members; (c) the withdrawal in liquidity provision is also greatest for algorithmic traders who are external customers of the exchange, and significantly less for algorithmic traders who are exchange members; and (d) the propensity of algorithmic traders to withdraw is strongly dependent and conditional on the extent of persistence of abnormal market conditions, consistent with the withdrawal of algorithmic traders being related to both the short horizon of such traders, and the potential constraints in the ability of pre-programmed algorithms to deal with the complexity of market signals in turbulent periods.

Second, we find that the withdrawal of algorithmic traders in stressful markets corresponds one-to-one with a loss of their informational advantage with respect to manual traders in such markets. This suggests that speed based information advantages of algorithmic traders disappear in the complexity of market signals in turbulent periods, and this motivates algorithmic traders to withdraw from voluntary liquidity provision in periods of stress.

Third, we also find the withdrawal of algorithmic traders has a significant propensity to generate feedback loops that can make markets more “fragile”. Specifically, we find that a reduction in algorithmic trading or algorithmic liquidity provision significantly increases the probability of extreme market conditions. The potential for fragility is further exacerbated by the fact that algorithmic traders in a stock withdraw significantly from that stock even in the absence of stressful conditions in that stock, when another similar sized stock experiences an *Extreme* event. The withdrawal of algorithmic traders hence displays significant contagion and correlation across stocks, even when stressful market conditions do not.

Overall, our results indicate that, in contrast to human traders adapting manually in (potentially higher latency) real time, ex-ante pre-programmed algorithmic trade execution is less conducive to low impact adjustment of complex information asymmetries or flows.

Hence, our results reinforce the extensive regulatory concerns that exist about the potential for systemic fragility created by algorithmic trading.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 documents the empirical results. Section 4 summarizes and offers concluding remarks.

2. Data and Variables Analyzed

NSE was created in 1994 as part of major economic reforms in India. It operates as pure electronic limit order book market and uses an automated screen based trading system that enables traders from across India to trade anonymously with one another on a real-time basis using satellite communication technology. NSE was the first exchange in the world to use satellite communication technology for trading. In terms of total number of trades, NSE is the second largest pure electronic LOB market in the world, just behind Shanghai Stock Exchange (SSE), and it is the fourth largest among all markets irrespective of market structure, behind NYSE, NASDAQ and SSE.[16] NSE 's order books accommodate all the standard types of orders that exist internationally in order-driven markets, including limit orders, market orders, hidden orders, stop-loss orders, etc. Limit orders can be continuously cancelled or modified without any incremental fees. NSE operates a continuous trading session from 9:00 am until 3:30 pm local time. The tick size is INR 0.05 (less than USD 0.01). Outstanding orders are not carried over to the next day. All spot trades are cleared with netting by novation at a clearing corporation and settled on a T + 2 basis. Algorithmic trading was introduced on the NSE in April, 2008. However, it was with the introduction of the co-location facility in January, 2010 that resulted in significant algorithmic trading on the NSE.

[16] World Federation of Exchanges, Annual Report, 2011

The sample consist of all the 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. The sample periods are two months, May 2006 and May 2012. Sample descriptive statistics for May 2012 are presented in Table 1. On average there are 454 trades and 28594 shares traded in a 5-minute interval. The dataset provides complete information of trades and orders that enables the reconstruction of the order book to obtain best quotes and depth information. *Spreads* are calculated using the best-ask and best-bid obtained from the order book, and are expressed as a percentage of the mid-quote. Order imbalances are calculated as the difference between buy-initiated and sell-initiated trading volume, and is expressed as a ratio of total trading volume. Trades are classified as buy-initiated or sell-initiated using information from the order book.

Further, the data also provides broad trader classifications. Traders classified as Client 1 and Client 3 are both customers of the exchange, but Client 3 traders employ their own Clearing Member – typically, entities that avail such a facility are foreign institutional investors, mutual funds, non-resident Indians, domestic corporations, and domestic financial institutions. Client 2 traders are members of the exchange and trade on behalf of their clients and also trade for their proprietary accounts. These traders generally function as voluntary intermediaries at the exchange[17]. The data also identify orders submitted using algorithms, with an 'Algo' flag. In all our univariate and multivariate analyses, we examine algorithmic trading using two measures – *participation* and *liquidity provision*. *Participation* is calculated as the average of the proportion of buy-side trading volume and the proportion of sell-side trading volume that involves an Algorithmic trader; and *liquidity provision* is calculated as the average of the proportion of buy-side trading volume and the proportion of sell-side trading volume for which AT provided liquidity. A trader is deemed to be supplying liquidity

[17] See www.nseindia.com/content/press/NSEbyelaws.pdf for further details.

when s/he is posting a standing limit order and demanding liquidity when s/he is "picking" an existing limit order through a market order or a marketable limit order. The greater the proportion of trading volume for which market makers are passive traders providing liquidity, the better the contribution to liquidity provision. All variables are calculated at 5-minute intervals.

Table 2 presents trading related sample statistics for AT and different trader categories. AT accounts for 38% of the trading volume and 16% of the liquidity provided on one side of the market – on an average, they trade 38% of the buy volume and sell volume each, and they provided liquidity on 16% of the buy and sell volume each (and demanded liquidity on the remaining 22% of their trading on each side of the book). Panel B of Table 2 presents *Participation* and *Liquidity Provision* by trader category. NSE members' proprietary trading account for a little over 25% of the trading volume, and it is almost equally split between AT and MT. Interestingly, Category 2 MT appear to be providing more liquidity than their automated peers. Category 1 traders account for 34% of the trading volume, of which 21% is automated. Once again, AT provide less liquidity per unit volume traded than their MT peers. Finally, Category 3 traders account for 41% of the trading volume, and are mostly MT.

3. Empirical Results

3.1. Overview of methodology

Market-makers are clearly expected to be reluctant to trade and provide liquidity during market crashes: for example, Floor Traders on the NYSE and Dealers in NASDAQ had both closed shop on 'Black Monday' October 19, 1987. But, AT, because of the inherent disadvantage in dealing with complex situations arising from electronic trading, and because of their objective to maximize their trading with minimal capital investment, could be extremely sensitive to even minor deviations from ‘normal’ conditions. It might not take a market-wide crash for AT to withdraw from the market: even small perturbations have the potential to instigate a withdrawal. In view of this conjecture, we examine the trading and liquidity provision of AT when market conditions deviate from the mean by greater than two standard deviations.

We study how algorithmic trading and liquidity provision change with market conditions, focusing specifically on periods of market stress - periods when market conditions (Eg: Volatility or Abs OIB) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as Volatility High when the 5-minute Volatility over the past 1 hour has been greater than twice its standard deviation, which is calculated over the sample period. Further, we classify a 5-minute time period as an Extreme period when either Volatility or Spreads or Absolute OIB over the past 1 hour has been greater than twice its in-sample standard deviation.

We also use the trader category provided in the dataset to conduct a Difference-in-Difference analysis to infer the effect of automation on trading characteristics in extreme market conditions. The objective here is to control for the type of the traders while examining algorithmic activity. For example, let’s say that category 1 MT reduce their liquidity provision from 20% in normal conditions to 15% in stressful conditions, and category 1 AT reduce their liquidity provision from 25% in normal conditions to 15% in stressful conditions. In such a case, we infer that, of the 10% drop in liquidity provision of category 1 AT, the algorithmic nature of trading is, in itself, responsible only for the incremental withdrawal in liquidity provision of 5%.

3.2. *Algorithmic trading activity in different market conditions: Univariate analysis*

This subsection provides the results of the univariate analysis of AT activity in different market conditions over the sample period, May 2012.

As reported in Table 3, the results provide strong and statistically significant conclusions. First, when volatility is persistently and significantly high, AT reduce their participation significantly – by 9.15 percentage points or 24%. Their overall liquidity provision in terms of posting of standing limit orders also falls significantly – from 16% to 12%, a 25% drop in liquidity provision. Second, when bid-ask spreads are significantly and persistently high, AT participation and liquidity provision again decrease significantly, by 18% each. Third, when absolute order imbalance is significantly and persistently high, the results are quite similar to the aforementioned conclusions in term of participation - it drops by 34%. However, the drop in liquidity provision - by 22% - is not statistically significant. The more toxic the order flow, the lower is the extent of participation by AT. Finally, and not surprisingly, periods classified as Extreme, also experience fairly large and statistically significant drops in participation and liquidity provision – by 21% each. Overall, the univariate analysis clearly indicates that AT tend to withdraw and provide less liquidity during stressful periods.

Table 3, Panel B provides results for the trading behavior of AT in extreme conditions that have not necessarily persisted for a relatively long time. In this table, we classify periods as Extreme when the market variables have been greater than two standard deviations for 30, 15 and 5 minutes (instead of one hour).

Our results show that the persistence of disturbances is an extremely important factor in the withdrawal of AT in extreme periods. Table 3, Panel B shows that, when turbulent conditions persisted for 5 minutes, algorithmic trading is mostly unaffected. We observe a significant drop in algorithmic trading and liquidity provision for persistence greater than 5 minutes. Moreover, the withdrawal of algorithmic trading and liquidity provision almost linearly increases with the persistence of market stress conditions. The more persistence there is, the greater the withdrawal in algorithmic trading and liquidity provision. Clearly, the propensity of algorithmic traders to withdraw is strongly dependent and conditional on the extent of persistence of abnormal market conditions, consistent with the withdrawal of algorithmic traders being related to both the short horizon of such traders, and the potential constraints in the ability of pre-programmed algorithms to deal with the complexity of market signals in turbulent periods.

Next, we examine whether the behavior of algorithmic traders is different in extreme conditions that are systematic in nature. To that extent algorithmic traders are unlikely to cause systematic stressful conditions, these tests arguably examine the change in algorithmic trading around exogenously created stressful conditions. To identify systematic events, we first decompose firm-level volatility, OIB and spreads into systematic and idiosyncratic components using simple market models. Next, we repeat the previous tests, but now on the systematic components of volatility, OIB and spreads. As shown in Table 4, the results show that AT withdraw and provide less liquidity even when the stressful conditions are systematic in nature. More specifically, AT withdraw more than 4.6 percentage points (or 12.1%) and provide 2.1 percentage points (or 13.3%) less liquidity during systematic extreme events. Results for extreme volatility and spread related events are qualitatively similar. Furthermore, as shown in Panel B, AT withdrawal monotonically increases with the persistence of the systematic stressful conditions.

In Table 5, we examine whether algorithmic trading changes differently in information related and liquidity related extreme events. A 5-minute period is classified as an *Information* related extreme event when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period and the corresponding *Spread* hasn’t. Similarly, a 5-minute period is classified as a *Liquidity* related extreme event when the

5-minute *Spread* over the past 1 hour has been greater than twice its standard deviation over the sample period and the corresponding *Volatility* hasn't. As expected, results show that AT withdrawal in terms of participation and liquidity provision is greater during information related extreme events than during liquidity related extreme events. More specifically, during information related extreme events, AT participation and liquidity provision drop by 9.2 percentage points (or 24.2%) and 3.9 percentage points (or 24.3%). Similarly, during liquidity related events, AT participation and liquidity provision drop by 6.62 percentage points (or 17.5%) and 2.8 percentage points (or 17.2%). Overall, irrespective of the nature of the stressful period (systematic or idiosyncratic, information or liquidity related) ATs significantly withdraw in terms of participation and liquidity provision.

A natural follow-up question is: don't all voluntary traders withdraw during periods of market stress? Hence, in our next analysis, we compare AT with other voluntary traders of the same trader-category. The difference-in-difference analysis of trading participation and liquidity provision provides a more robust understanding of incremental influence of automation on trading strategies. The results are presented in Table 6.

In Panel A, the control group consists of manual traders in May, 2012, and in Panel B, all traders from May, 2006 are used as a control group. *Extreme* periods in the May, 2006 sample are identified as they are in the May, 2012 sample. In both the periods the control group consists of voluntary traders that operate in electronic markets. Hence, the difference-in-difference analysis yields a clean estimate of the effect of automation on trading strategies. Panel A presents numerous results. First, category 1 traders significantly withdraw during periods of market stress. However, category 1 AT traders withdraw significantly withdraw more than the category 1 MT traders. More specifically, participation rate of category 1 AT drops by 9.1 percentage points, which is 1.3 times the same variable for category 1 MT traders; similarly liquidity provision decreases by 4.6 percentage points, which is more than 5 times the same for MT category 1 traders. These results clearly show that, even after controlling for trader fixed effects, voluntary automated traders are more sensitive to extreme events than their MT peers. Second, similar to category 1 case, algorithmic category 3 traders also withdraw significantly more than their MT peers in terms of trading participation and liquidity provision; but AT themselves don’t change their trading activity significantly during extreme events. Had we only analyzed algorithmic trading of category 2 traders, we would have inferred that they don’t leave the markets in stressful conditions! However, after we control for general trading characteristics of their peers, we observe that the incremental effect of automation is negative and significant. Finally, category 2 traders provide a very different story. Here, we find no significant difference in the way AT and MT react to extreme events, and also that category 2 AT significantly increase their liquidity provision in stressful market condition. Significant difference between sell-side (category 2) and buy-side (category 1and 3) AT during extreme events highlights the heterogeneity amongst AT (Hagströmer and Nordén, 2013). Also, sell-side algorithms are more concerned about the reputational costs of withdrawing liquidity when it is required the most.

Results in Panel B are qualitatively similar to those presented in Panel A – category 1 algorithmic traders withdraw liquidity the most and category 2 algorithmic traders withdraw the least. Again, category 1 algorithmic traders withdraw significantly more than the control sample during stressful market conditions – automation adversely affects liquidity provision. Also, interestingly, category 1 traders in 2006 increase their *Participation* and *Liquidity Provision* during *Extreme* events. As reported in Panel A, even manual traders in 2012 withdraw during periods of stress. Algorithmic traders appears to have adversely affected the ‘ecology’ of the market itself. Further, category 2 algorithmic traders significantly increase their trading activity and liquidity provision more than their control sample. This results further highlights the differences between buy-side and sell-side algorithmic traders and the inherent heterogeneity amongst algorithmic traders. Finally, we do not find any significant difference between category 2 algorithmic traders in 2012 and category 2 traders in 2006.

3.3.Algorithmic trading activity in different market conditions: Multivariate Analysis

In this section, we again examine the changing nature of algorithmic trading during periods of market stress, but in a multivariate setting. To this end, we regress algorithmic Participation and Liquidity Provision during a 5-minute interval on market quality variables – spreads, volatility and absolute order imbalance – and other control variables – returns and total trading volume. All these independent variables are calculated using data from the past hour, and they are also standardized by stock. We also control for time-of-the-day effects by including a dummy variable for the opening and closing hours each.

Results from the analysis, presented in Table 7, further confirm the previously discussed univariate results. First, algorithmic trading Participation and Liquidity Provision both drop significantly in Extreme conditions – by 0.2 standard deviations each. Second, algorithmic participation decreases with volatility, but increases when volatility is very high. However, the increased participation appears to be a liquidity demanding one, as reported in Liquidity Provision results – algorithmic Liquidity Provision drops significantly when volatility is high. Third, algorithmic participation is only related to spreads when they are very large – and the relation is negative and significant. Algorithmic Liquidity Provision is positively related to spreads, but the relation is reversed when Spreads are very large. Algorithmic traders turn from liquidity providers to liquidity demanders when the demand for liquidity is high. Finally, Participation and Liquidity Provision are negatively related to Abs OIB - even a moderate increase is negatively related. To the extent absolute OIB is a proxy for informed order flow, algorithms appear to be extremely sensitive to toxic order flow. In sum, irrespective of the variable used to identify periods of market stress, AT appear to withdrawing participation and liquidity during periods of market stress - precisely when liquidity and intermediation are needed the most.

Table 8 presents results of a similar analysis, except that the dependent variables are ∆Participation and ∆ Liquidity Provision - difference between Participation and Liquidity Provision of AT and MT of the same client category in a given 5-minute interval respectively. Instead of explaining the algorithmic trading itself, we examine and explain the difference in trading activity of AT and MT belonging to the same trader classification. Hence, the dependent variable here is a more robust measure of the incremental effect of automation on trading strategies. The results are mostly consistent with those presented in the previous tables. Algorithmic traders withdraw significantly more than their MT peers during Extreme events in general; more specifically, they are significantly more sensitive to wide spreads and large (absolute) order imbalances. However, they do not withdraw liquidity significantly more than their MT peers during periods of high volatility. Overall, these results provide strong confirmation that AT significantly reduce their contribution to liquidity provision in periods of market stress.

3.4.Limit order activity of algorithmic traders and market conditions

An important question following the analysis of AT trading is whether reduction in algorithmic trades during extreme conditions is because of their withdrawal from the order book, or due to algorithmic traders posting relative more passive orders. This subsection focuses on AT limit order activity in different market conditions over the sample period, May 2012. AT limit order activity is measured as the proportion of the number and the volume of new orders submitted by algorithmic traders; and the proportion of the number and volume of net-new orders (new orders minus cancelled orders) submitted by algorithmic traders.

We first analyze and discuss the withdrawal of algorithmic traders from the order book during extreme conditions. Our results, presented in Table 9, show that AT withdrawal activity in the order book during extreme conditions is very similar to their withdrawal activity in the trade book. First, when volatility is persistently and significantly high, AT reduce their participation in terms of new orders significantly – by 8.93 percentage points or 18%; and in terms of net new orders by 13 percentage points or 31%. The volume of new and net-new algorithmic orders also drops during extreme market conditions – by 21% and 48% respectively. Second, when bid-ask spreads are significantly and persistently high, AT new orders and net-new orders decrease significantly, by 12 and 17 percentage points (or 26% and 42%) respectively; and volume of new and net-new orders also drop similarly. Third, when absolute order imbalance is significantly and persistently high, the results are quite similar to the aforementioned conclusions in term of number and volume of new and net-new orders. However, the drop in volume of net-new orders - by 37% - is not statistically significant. Finally, and not surprisingly, periods classified as 'Extreme' also experience fairly large and statistically significant drops in limit order activity. The proportion of new and net-new orders drops significantly by 22% and 36% respectively. The drops in the proportion of the volume of new and net-new orders – by 18% and 46% - are also statistically highly significant.

Next, we analyze the change in the relative pricing or aggressiveness of the new algorithmic and manual orders that are actually submitted during periods of market stress. The aim of this analysis is to examine whether the reduction in AT trades (relative to MT) also because AT's orders reflect a higher price for liquidity supply services. Our results are in the last column of Table 9. Clearly, the change in the relative aggressiveness of orders is not statistically significant in this specification.

Overall, our univariate analysis clearly indicates that, in addition to the significant drop in the numbers of algorithmic trades during extreme conditions, AT also withdraw heavily from the order book itself during stressful periods, instead of just posting less aggressive orders.

Similar to the analysis of trades, we next employ a difference-in-difference analysis of algorithmic activity, where the control group consists of the same category of manual traders, to provide a cleaner analysis of the incremental influence of automation on limit order book activity. As seen from Table 10, the analysis provides various important results. Most importantly, all categories of AT withdraw significantly more than their MT counterparts. First, for category 1 ATs, the proportion of new orders and net-new orders, drops dramatically by 6 and 11 percentage points respectively, which are 8.4 and 6.1 times the corresponding variable for category 1 MT traders. Similarly the volume of new and net-new orders decreases massively by 4 and 18.1 percentage points, which are 4.7 and 2.7 times the corresponding variable for MT category 1 traders. Second, even though category 3 AT don't change their *trading* activity significantly during extreme events, algorithmic category 3 traders withdraw significantly more than their MT peers in terms of new and net-new orders. Third, algorithmic category 2 traders withdraw the least, but they also withdraw very significantly more than their MT peers.

As before, we also analyze, separately for each category of traders, the change in the relative pricing of limit orders for the traders who actually place orders. The results are in the last column of Table 10, and are much more conclusive than with the lower power overall analyses earlier in the last column of Table 9. Here, we find that category 1 and 3 ATs that remain in the market place significantly less aggressive orders than their manual peers in stressful conditions, effectively increasing the price at which they are willing to supply liquidity. However, there is no significant change in the relative aggressiveness of orders placed by category 2 ATs, i.e., exchange members. These results are consistent with the results of our analysis of algorithmic trades, which showed that category 2 ATs do not also significantly withdraw during stressful market conditions in terms of trade participation. That said, as discussed in the foregoing paragraph, category 2 traders do reduce the flow of new orders significantly more than corresponding MT category 2 traders. The differences between category 2 and other trader categories further underline the importance of understanding heterogeneity amongst AT (Hagströmer and Nordén, 2013).

Overall, to summarize, the results in this section clearly show that all categories of voluntary automated traders withdraw from the order book significantly more than their manual peers during stressful market conditions; and furthermore, with the exception of exchange members, also place orders that are significantly less aggressive than the orders of the corresponding group of manual traders.

3.5.Informativeness of algorithmic traders and market conditions

In this section, we examine whether, in accordance with the complexity hypothesis, AT lose their informational advantage during periods of persistent market stress, which arguably display a more complex financial environment. Informativeness is first calculated for each trade and then it is aggregated for a trader category during a 5-minute interval. For buys, price change is measured as the midquote prevailing 5 min (15, 30 or 60 min) after transaction less the buy price, expressed as a ratio of the buy price. For sells, price change is measured as the sell price less the midquote 5 min (15, 30 or 60 min) after order submission, expressed as a ratio of the sell price. Informativeness for a trader category during a 5-minte interval is calculated as the volume weighted average of all price changes relating to the trader category during the 5-minutes interval.

Our results, presented in Table 11 Panel A, provide various insights. First, consistent with the extant literature, we find that, in ‘normal’ conditions, AT are significantly more informed than MT; and their informational advantage manifests over all time horizons we analyze, ranging from 5 minutes to 60 minutes. Moreover, MT appear to be consistently losing money over all horizons. The situation is drastically reversed in 'Extreme' periods. Here, AT are negatively informed over all horizons except for the very short-term. Manual traders, however, are significantly informed over all horizons. The difference between AT and their MT peers is significantly negative over all horizons. The difference-in-difference in informativeness unambiguously conveys that AT significantly lose their informational advantage during periods of market stress – evidence that strongly supports the complexity hypothesis.

Panel B, C and D provide results for scenarios when extreme conditions persist for 30-minute, 15-minute and 5-minute periods. In these panels, we classify periods as *Extreme* when the market variables have been greater than two standard deviations for 30, 15 and 5 minutes (instead of one hour) respectively. Consistent with our previous results, this analysis also shows that the persistence of disturbances is an important factor. Panel D shows that, when turbulent conditions persisted for 5 minutes, the informativeness of algorithmic trading is mostly unaffected. However, we observe a significant drop in the informativeness of algorithmic trades when extreme conditions persist for more than 15 minutes. The more persistent an event, the greater is the reversal in the relative informativeness of algorithmic traders. This evidence again strongly supports the complexity hypothesis.

Next, in Table 12, we present results of a similar analysis, but the differences in informativeness are calculated between AT and MT of the same trader category. Such an analysis not only controls for trader fixed effects, but also enables a buy-side vs. sell-side comparison of AT. Stressful periods are defined based on persistence of volatility, spreads, and/or order imbalances for 60 minutes. The results show that the conclusions from Table 11 are driven by category 1 algorithmic traders. Trader category 1 AT are the group that significantly lose their level of informativeness during extreme conditions to category 1 MT. Category 2 AT do not display any informativeness in either normal or stressful periods, but, since category 2 MT lose their informativeness in stressful periods, category 2 AT appear to perform relatively better in such stressful periods. Similarly, category 3 traders – whether they are AT or MT – do not display any informativeness in any period, and there is no significant change in relative informativeness of category 3 AT. Each of these results are robust to both short and long-term horizons.

Overall, our results in this section show that there is a close correspondence between the change in informativeness and the change in participation and liquidity provision of AT. This close correspondence strongly supports the complexity hypothesis. Though we have not formally established causality, our results suggest that AT exit markets during periods of market stress because they lose their informational competitive advantage.

3.6.Probability of extreme events and algorithmic trading

Having seen that AT withdraw Participation and Liquidity Provision in extreme conditions, we analyze if their withdrawal in turn further increases the probability of observing an extreme event in the next 5-minute interval. This analysis speaks directly to the issue of market fragility. A vicious circle of AT withdrawal and extreme events could quickly destabilize markets. Logit models are used to explain the probability of observing an extreme event in the next 5-minute interval as a function of algorithmic traders' Participation and Liquidity Provision and other pertinent variables over the past hour. Our results are presented in Table 13.

Our results show that, across all specifications, as AT withdraw from trading and/or liquidity provision, the probability of observing an extreme event in the next 5 minute interval increases significantly. Of course, extreme events are persistent by design, hence we also control for prevailing market conditions – volatility, spreads, absolute OIB, volume and returns. Our results show that even after controlling for the persistent nature of extreme market conditions, algorithmic traders' withdrawal significantly increases the probability of extreme events. A one standard deviation decrease in Participation increases the odds of an extreme event by at least 28%; and a one standard deviation decrease in Liquidity Provision increases the odds of an extreme event by at least 30%.

3.7. Algorithmic trading, extreme events and contagion

In this subsection, we examine whether the withdrawal of algorithmic trading and liquidity provision during stressful conditions documented earlier also spreads across to stocks that haven't experienced extreme events. Once again, an analysis of the contagion effects of withdrawal of algorithmic traders speaks directly to the issue of market fragility. To this end, a 5-minute interval, for stock *i*, is classified as an *Extreme-Contagion* event when any stock j (< > *i*) has an *Extreme* event during the same 5-minute interval, but stock *i* itself does not. Volatility, OIB and spreads related contagion events are similarly identified.

The results of this analysis are presented in Table 14. The results clearly show that, conditional on any one stock experiencing an extreme market conditions during a 5-minute interval, algorithmic traders significantly withdraw in terms of participation and liquidity provision even in stocks not experiencing stressful market conditions during the 5-minute interval. More specifically, AT reduce their participation and liquidity provision significantly – by 2.8 percentage points (or 7.4%) and 0.8 percentage points (or 4.9%). Similarly, as shown in the table, withdrawal in algorithmic trading and liquidity provision during contagion events is statistically and economically significant for volatility, OIB and spread related events as well.

4. Concluding Remarks

We empirically investigate whether the participation and transactional liquidity provided by algorithmic traders – i.e., posting of standing buy and sell limit orders that have provided trade execution and immediacy to other traders – is as reliable and stable as that of human traders even in times of market stress; or whether algorithmic traders are just the "fair weather" liquidity suppliers they are sometimes feared by regulators to be.

We document results of considerable academic and regulatory importance. First, we find strong evidence that, in contrast to manual traders, algorithmic traders reduce their participation and their transactional liquidity provision in periods of significantly high and persistent volatility, significantly high and persistent customer order imbalances, and significantly high and persistent bid ask spreads. There are several aspects of this result that are noteworthy: (a) the reduction in transactional liquidity provision is accompanied also by a significantly greater magnitude of reduction in the placement of new orders by all categories of algorithmic traders (relative to the manual traders in each of those categories); (b) the reduction in transactional liquidity provision is also accompanied by a decrease in the aggressiveness of all algorithmically posted orders (relative to the corresponding aggressiveness of manually posted orders), except for algorithmic orders of exchange members; (c) the withdrawal in liquidity provision is also greatest for algorithmic traders who are external customers of the exchange, and significantly less for algorithmic traders who are exchange members; and (d) the propensity of algorithmic traders to withdraw is strongly dependent and conditional on the extent of persistence of abnormal market conditions, consistent with the withdrawal of algorithmic traders being related to both the short horizon of such traders, and the potential constraints in the ability of pre-programmed algorithms to deal with the complexity of market signals in turbulent periods.

Second, we also find that the withdrawal of algorithmic traders in stressful markets corresponds one-to-one with a loss of their informational advantage with respect to manual traders in such markets. This suggests that the speed based information advantages of algorithmic traders disappear in the complexity of market signals in turbulent periods, and this motivates algorithmic traders to withdraw from voluntary liquidity provision in periods of stress.

Third, we also find the withdrawal of algorithmic traders has a significant propensity to generate feedback loops that can make markets more “fragile”. Specifically, we find that a reduction in algorithmic trading or algorithmic liquidity provision significantly increases the probability of extreme market conditions. The potential for fragility is further exacerbated by the fact that algorithmic traders in a stock withdraw significantly from that stock even in the absence of stressful conditions in that stock, when another similar sized stock experiences an *Extreme* event. The withdrawal of algorithmic traders hence displays significant contagion and correlation across stocks, even when stressful market conditions do not.

Overall, our results indicate that, in contrast to human traders adapting manually in (potentially higher latency) real time, ex-ante pre-programmed algorithmic trade execution is less conducive to low impact adjustment of severe information asymmetries or high intensity information flows. Hence, our results reinforce the extensive regulatory concerns that exist about the potential for systemic fragility created by algorithmic trading.

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Table 1 – Sample Description

This table presents market characteristics for the time-period May, 2012. All market variables are calculated over 5 minute intervals. Volatility, Return, (Bid-Ask) Spread, Volume and (relative) Order Imbalances (OIB) are calculated as done in the literature.

	Volatility	Return	Spreads	Volume	#Trades	OIB	Abs OIB
Mean	0.49%	-0.01%	0.15%	28597.64	454.132	-1.32%	33.58%
Median	0.09%	0.00%	0.05%	10046	256	-1.64%	26.66%
Std	9.39%	9.41%	7.69%	73099.52	696.442	43.08%	27.01%
P25	0.03%	-0.10%	0.03%	2616	86	-28.40%	12.30%
P75	0.20%	0.09%	0.08%	29688	573	24.87%	47.65%

Table 2 – Algorithmic Trading Description

This table presents characteristics of Algorithmic trading for the time-period May, 2012. All market variables are calculated over 5 minute intervals. Traders are classified into three client categories by NSE (National Stock Exchange). *Algo* is a binary variable that identifies algorithmic messages. Traders classified as Client 1 and Client 3 are both customers of the exchange, but Client 3 traders employ their own Clearing Member –typically, entities that avail such a facility FIIs, Mutual Funds, NRIs, Domestic Body Corporates & Domestic Financial Institutions etc. Client 2 traders are members of the exchange. *Participation* is the proportion of trading volume that involves an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade.

Panel A: Algo Participation and Liquidity Provision

Algo	Participation	Liquidity Provision
1	37.77%	16.07%
0	62.23%	33.94%

Panel B: Algo Participation and Liquidity Provision by trader category

Clients	Algo	Participation	Liquidity Provision
1- Customers	1	21.14%	10.54%
	0	12.68%	7.62%
3- Customers with Special Custodians	1	4.11%	2.56%
	0	36.69%	18.47%
2- NSE Members	1	12.52%	2.96%
	0	12.86%	7.85%

Table 3 – Algorithmic Trading by Market Conditions – Univariate Analysis

This table presents univariate analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. Panel B reports results from similar analysis when *Extreme* conditions are identified based on 30, 15 and 5 minute persistence of high *Volatility* or *Spreads* or *Absolute OIB*. *Algo* is a binary variable that identifies algorithmic messages. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Panel A: 1 Hour Persistence

Market Conditions	N	Participation	Liquidity Provision
Extreme Conditions	347	29.62%	12.66%
Normal Conditions	62638	37.82%	16.08%
Difference		-8.20%	-3.42%
t-stat		*-7.96*	*-5.88*
Volatility High	201	28.65%	12.07%
Volatility Otherwise	62784	37.80%	16.08%
Difference		-9.15%	-4.01%
t-stat		*-6.78*	*-5.25*
Spreads High	141	30.94%	13.07%
Spreads Otherwise	62844	37.79%	16.07%
Difference		-6.85%	-3.00%
t-stat		*-4.25*	*-3.3*
Abs OIB High	10	24.81%	12.60%
Abs OIB Otherwise	62975	37.77%	16.07%
Difference		-12.96%	-3.47%
t-stat		*-2.14*	*-1.01*

Panel B: Shorter Persistence

Market Conditions	N	Participation	Liquidity Provision
30 min Persistence			
Extreme Conditions	960	33.51%	15.01%
Normal Conditions	62025	37.84%	16.08%
Difference		-4.33%	-1.07%
t-stat		*-6.96*	*-3.05*
15 min Persistence			
Extreme Conditions	1790	34.48%	15.21%
Normal Conditions	61195	37.87%	16.09%
Difference		-3.39%	-0.88%
t-stat		*-7.38*	*-3.41*
5 min Persistence			
Extreme Conditions	5128	37.26%	16.26%
Normal Conditions	57857	37.82%	16.05%
Difference		-0.56%	0.21%
t-stat		*-2*	*1.37*

Table 4 – Algorithmic Trading and Systematic Events – Univariate Analysis

This table presents univariate analysis of algorithmic trades during periods of systematic market stress- periods when the systematic component of market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the systematic component of 5-minute *Volatility* (estimated through a market model) over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when the systematic component of either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. Panel B reports results from similar analysis when *Extreme* conditions are identified based on 30, 15 and 5 minute persistence. *Algo* is a binary variable that identifies algorithmic messages. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Panel A: 1 Hour Persistence

Market Conditions	N	Participation	Liquidity Provision
Extreme Conditions	167	33.22%	13.94%
Normal Conditions	62818	37.78%	16.07%
Difference		-4.56%	-2.13%
t-stat		*-3.08*	*-2.55*
Volatility High	133	34.78%	14.90%
Volatility Otherwise	62852	37.78%	16.07%
Difference		-3.00%	-1.17%
t-stat		*-1.8*	*-1.25*
Spreads High	34	27.09%	10.19%
Spreads Otherwise	62951	37.78%	16.07%
Difference		-10.69%	-5.88%
t-stat		*-3.26*	*-3.17*

Panel B: Shorter Persistence

Market Conditions	N	Participation	Liquidity Provision
30 min disturbances			
Extreme Conditions	1292	34.39%	15.18%
Normal Conditions	61693	37.84%	16.08%
Difference		-3.45%	-0.90%
t-stat		*-6.42*	*-2.96*
15 min disturbances			
Extreme Conditions	4325	36.36%	15.65%
Normal Conditions	58660	37.88%	16.10%
Difference		-1.52%	-0.45%
t-stat		*-5.04*	*-2.63*
5 min disturbances			
Extreme Conditions	6966	37.53%	15.99%
Normal Conditions	56019	37.80%	16.07%
Difference		-0.27%	-0.08%
t-stat		*-1.13*	*0.58*

Table 5 – Algorithmic Trading, Information and Liquidity Events – Univariate Analysis

This table presents univariate analysis of algorithmic trades during periods of information and liquidity related market stress. A 5-minute period is classified as an *Information* related extreme event when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period and the corresponding *Spread* hasn't. Similarly, a 5-minute period is classified as a *Liquidity* related extreme event when the 5-minute *Spread* over the past 1 hour has been greater than twice its standard deviation over the sample period and the corresponding *Volatility* hasn't. *Algo* is a binary variable that identifies algorithmic messages. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Market Conditions	N	Participation	Liquidity Provision
Extreme Conditions - Information	194	28.65%	12.18%
Normal Conditions	62791	37.80%	16.08%
Difference		-9.15%	-3.90%
t-stat		*-6.66*	*-5.01*
Extreme Conditions - Liquidity	131	31.17%	13.31%
Volatility Otherwise	62854	37.79%	16.07%
Difference		-6.62%	-2.76%
t-stat		*-3.96*	*-2.92*

Table 6 – Algorithmic Trading by Market Conditions – Difference-in-Difference Analysis

This table presents a difference-in-difference analysis of algorithmic trades during periods of market stress-periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. Traders classified as Client 1 and Client 3 are both customers of the exchange, but Client 3 traders employ their own Clearing Member – typically, entities that avail such a facility FIIs, Mutual Funds, NRIs, Domestic Body Corporates & Domestic Financial Institutions etc. Client 2 traders are member of the exchange. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. In Panel A, the analysis is conducted using data only from May, 2012. In Panel B, the analysis employs data from both 2006, May and 2012. *t*-statistics are also reported.

Panel A

Client	Algo	Market Conditions	N	Participation	Liquidity Provision
1	1	Extreme	347	12.1%	5.9%
1	1	Otherwise	62638	21.2%	10.6%
		Difference		-9.1%	-4.6%
		t-stat		*-9.50*	*-8.37*
1	0	Extreme	347	8.9%	5.6%
1	0	Otherwise	62638	12.7%	7.6%
		Difference		-3.9%	-2.0%
		t-stat		*-4.59*	*-3.72*
		Difference-in-Difference		-5.21%	-2.60%
		t-stat		*-4.10*	*-3.32*
3	1	Extreme	347	4.6%	2.8%
3	1	Otherwise	62638	4.1%	2.6%
		Difference		0.5%	0.2%
		t-stat		*1.68*	*1.07*
3	*0*	*Extreme*	*347*	*46.9%*	*23.3%*
3	0	Otherwise	62638	36.6%	18.4%
		Difference		10.3%	4.8%
		t-stat		*9.22*	*7.61*
		Difference-in-Difference		-9.76%	-4.63%
		t-stat		*-8.49*	*-6.99*
2	1	Extreme	347	12.9%	4.0%
2	1	Otherwise	62638	12.5%	3.0%
		Difference		0.4%	1.0%
		t-stat		*-0.71*	*-4.87*
2	0	Extreme	347	14.6%	8.5%
2	0	Otherwise	62638	12.9%	7.8%
		Difference		1.8%	0.6%
		t-stat		*-2.86*	*-1.42*
		Difference-in-Difference		-1.43%	0.38%
		t-stat		*-1.75*	*0.80*

Panel B

Client	Year	Algo	Market Conditions	N	Participation	Liquidity Provision
1	2012	1	Extreme	347	12.1%	5.9%
1		1	Otherwise	62638	21.2%	10.6%
			Difference		-9.1%	-4.6%
			t-stat		*-9.50*	*-8.37*
1	2006	0	Extreme	1294	32.7%	18.3%
1		0	Otherwise	70384	29.2%	16.3%
			Difference		3.5%	2.1%
			t-stat		*5.26*	*5.15*
			Difference-in-Difference		-12.54%	-6.71%
			t-stat		*-15.28*	*-13.85*
3	2012	1	Extreme	347	4.6%	2.8%
3		1	Otherwise	62638	4.1%	2.6%
			Difference		0.5%	0.2%
			t-stat		*1.68*	*1.07*
3	2006	0	Extreme	1294	43.1%	19.8%
3		0	Otherwise	70384	43.5%	20.7%
			Difference		-0.4%	-0.9%
			t-stat		*-0.63*	*-2.65*
			Difference-in-Difference		0.86%	1.09%
			t-stat		*1.89*	*1.55*
2	2012	1	Extreme	347	12.9%	4.0%
2		1	Otherwise	62638	12.5%	3.0%
			Difference		0.4%	1.0%
			t-stat		*0.71*	*4.87*
2	2006	0	Extreme	1294	24.3%	11.9%
2		0	Otherwise	70384	27.4%	13.0%
			Difference		-3.1%	-1.2%
			t-stat		*-7.63*	*-4.62*
			Difference-in-Difference		3.48%	2.19%
			t-stat		*7.56*	*9.41*

Table 7 – Algorithmic Trading by Market Conditions – Multivariate Analysis

This table presents regression analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time Periods of market stress are identified as periods when market conditions (Eg: *Volatility* or *CD Imbalance*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example *Volatility High* is a binary variable equal to 1 when 5-min *Volatility* (and/or *CD Imbalance*) over the past 1 hour has been greater than twice its standard deviation over the sample period. *Extreme Conditions* is a binary variable equal to 1 when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. All variables are standardized by stock and calculated using the previous hour's data. The analysis is conducted using data from May, 2012. *t*-statistics are reported below coefficient estimates.

	Participation			Liquidity Provision		
A	0.05	0.05	0.05	0.02	0.03	0.03
	10.00	*10.12*	*9.88*	*4.96*	*5.70*	*5.93*
Extreme Conditions	-0.21			-0.21		
	-3.84			*-3.90*		
Volatility		-0.09	-0.10		-0.01	0.01
		-8.62	*-8.46*		*-0.66*	*0.65*
*Volatility*Volatility High*			0.04			-0.05
			2.00			*-2.35*
Spreads		0.00	0.01		0.01	0.02
		0.32	*0.79*		*1.02*	*1.71*
*Spreads*Spreads High*			-0.05			-0.06
			-1.70			*-2.10*
Abs OIB		-0.23	-0.23		-0.24	-0.24
		-22.90	*-22.73*		*-24.49*	*-23.99*
*Abs OIB*Abs OIB High*			-0.24			-0.03
			-1.81			*-0.22*
Return		-0.03	-0.03		-0.02	-0.02
		-2.07	*-2.16*		*-1.68*	*-1.87*
Volume	-0.01	-0.01	-0.01	0.05	0.02	0.02
	-0.71	*-0.68*	*-0.70*	*5.98*	*2.29*	*2.13*
Open	-0.38	-0.39	-0.38	-0.24	-0.28	-0.28
	-29.90	*-30.23*	*-29.53*	*-19.04*	*-21.47*	*-21.34*
Close	0.01	0.01	0.01	0.05	0.05	0.05
	0.68	*0.72*	*0.83*	*4.80*	*4.68*	*4.56*
Adj. R-square	1.70%	2.52%	2.54%	0.75%	1.68%	1.70%
# Observations	62985	62985	62985	62985	62985	62985

Table 8 – Algorithmic Trading by Market Conditions – Difference-in-Difference Multivariate Analysis

This table presents regression analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time Periods of market stress are identified as periods when market conditions (Eg: *Volatility* or *CD Imbalance*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example *Volatility High* is a binary variable equal to 1 when 5-min *Volatility* (and/or *CD Imbalance*) over the past 1 hour has been greater than twice its standard deviation over the sample period. *Extreme Conditions* is a binary variable equal to 1 when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. Δ*Participation* is the difference between *Participation* of algorithmic and manual traders of the same client category in a 5-min interval. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. Δ *Liquidity Provision* is the difference between *Liquidity Provision* of algorithmic and manual traders of the same client category in a 5-min interval. All variables are standardized by stock and calculated using the previous hour's data. The analysis is conducted using data from May, 2012. *t*-statistics are reported below coefficient estimates.

	ΔParticipation			ΔLiquidity Provision		
α	0.04	0.04	0.04	0.02	0.02	0.02
	13.36	*13.37*	*13.04*	*7.66*	*7.99*	*8.04*
Extreme Conditions	-0.10			-0.10		
	-3.28			*-3.28*		
Volatility		-0.05	-0.06		-0.01	-0.01
		-7.57	*-7.89*		*-1.51*	*-0.88*
*Volatility*Volatility High*			0.03			-0.01
			2.75			*-0.70*
Spreads		0.00	0.01		0.01	0.01
		0.53	*1.06*		*1.10*	*1.89*
*Spreads*Spreads High*			-0.04			-0.04
			-2.19			*-2.54*
Abs OIB		-0.11	-0.11		-0.09	-0.09
		-18.63	*-18.46*		*-15.69*	*-15.36*
*Abs OIB*Abs OIB High*			-0.24			-0.06
			-3.05			*-0.80*
Return		-0.02	-0.03		-0.02	-0.02
		-3.14	*-3.26*		*-2.79*	*-2.98*
Volume	0.00	0.00	0.00	0.05	0.04	0.04
	-0.80	*-0.58*	*-0.60*	*10.25*	*7.75*	*7.61*
Open	-0.27	-0.28	-0.27	-0.18	-0.20	-0.20
	-37.46	*-37.20*	*-36.27*	*-25.11*	*-26.11*	*-25.71*
Close	-0.01	-0.01	-0.01	0.02	0.02	0.02
Adj. R-square	0.87%	1.06%	1.07%	0.40%	0.52%	0.53%
# Observations	188955	188955	188955	188955	188955	188955

Table 9 – Order Placements by Algorithmic Traders and Market Conditions – Univariate Analysis

This table presents univariate analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour have been greater than twice their standard deviation calculated over the sample period. *New Orders* is the ratio of the number new orders placed by algorithmic traders and total number of new orders placed in a 5-minute period. *Net New Orders* is the ratio of net new orders (new orders minus cancelled orders) placed by algorithmic traders and total number of net new orders placed in a 5-minute period. *Volume of New Orders* is the ratio of the volume of new orders placed by algorithmic traders and total volume of new orders placed in a 5-minute period. *Volume of Net New Orders* is the ratio of the volume of net new orders (new orders minus cancelled orders) placed by algorithmic traders and total volume of new orders placed in a 5-minute period. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Market Conditions	N	New Orders	Net New Orders	Volume of New Orders	Volume of Net New Orders	N	Relative Prices
Extreme Conditions	347	39.09%	26.93%	41.18%	22.60%	330	3.63%
Normal Conditions	69208	49.86%	41.95%	50.32%	42.05%	66639	2.80%
Difference		-10.77%	-15.02%	-9.14%	-19.45%		0.83%
t-stat		*-9.04*	*-5.25*	*-6.64*	*-7.89*		*0.33*
Volatility High	201	40.90%	28.84%	39.82%	21.95%	201	3.90%
Volatility Otherwise	69354	49.83%	41.91%	50.31%	42.01%	66768	2.81%
Difference		-8.93%	-13.07%	-10.49%	-20.06%		1.09%
t-stat		*5.71*	*3.48*	*5.80*	*6.94*		*-0.34*
Spreads High	141	37.61%	24.40%	43.18%	22.42%	130	3.30%
Spreads Otherwise	69414	49.83%	41.91%	50.29%	41.99%	66839	2.81%
Difference		-12.22%	-17.51%	-7.11%	-19.57%		0.49%
t-stat		*6.54*	*3.91*	*3.30*	*6.68*		*-0.92*
OIB High	10	12.88%	11.36%	23.27%	26.15%	3	2.81%
OIB Otherwise	69545	49.80%	41.87%	50.28%	41.94%	66966	0.84%
Difference		-36.92%	-30.51%	-27.01%	-15.79%		1.97%
t-stat		*-5.273*	*-5.07*	*-3.338*	*-1.17*		*3.25*

Table 10 – Order Placements by Algorithmic Traders and Market Conditions – Difference-in-Difference Analysis

This table presents a difference-in-difference analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. Traders classified as Client 1 and Client 3 are both customers of the exchange, but Client 3 traders employ their own Clearing Member –typically, entities that avail such a facility FIIs, Mutual Funds, NRIs, Domestic Body Corporates & Domestic Financial Institutions etc. Client 2 traders are member of the exchange. *New Orders*, for a class of traders, is the ratio of the number new orders placed by the corresponding class of traders and total number of new orders placed in a 5-minute period. *Net New Orders*, for a class of traders, is the ratio of net new orders (new orders minus cancelled orders) placed by the corresponding class of traders and the total number of net new orders placed in a 5-minute period. *Volume of New Orders*, for a class of traders, is the ratio of the volume of new orders placed by the corresponding class of traders and the total volume of new orders placed in a 5-minute period. *Volume of Net New Orders*, for a class of traders, is the ratio of the volume of net new orders (new orders minus cancelled orders) placed by the corresponding class of traders and the total volume of new orders placed in a 5-minute period. *t*-statistics are also reported.

Client	Algo	Market Conditions	N	New Orders	Net New Orders	Volume of New Orders	Volume of Net New Orders	N	Relative Prices
1	1	Extreme Conditions	347	8.00%	10.90%	4.40%	11.11%	156	0.26%
1	1	Normal Conditions	61516	13.95%	21.61%	8.35%	29.25%	27423	6.65%
		Difference		-5.95%	-10.71%	-3.95%	-18.14%		-6.39%
		t-stat		*-6.53*	*-3.78*	*-5.32*	*-1.97*		*-2.97*
1	0	Extreme Conditions	347	1.11%	1.36%	3.21%	6.60%		
1	0	Normal Conditions	61516	1.82%	3.11%	4.06%	13.44%		
		Difference		-0.71%	-1.75%	-0.85%	-6.84%		
		t-stat		*-2.97*	*-3.71*	*-7.73*	*-0.70*		
		Difference-in-Difference		-5.24%	-8.96%	-3.10%	-11.30%		
		t-stat		*-8.27*	*-9.60*	*-5.21*	*-3.65*		
2	1	Extreme Conditions	347	24.86%	11.63%	32.08%	8.18%	322	1.23%
2	1	Normal Conditions	61516	29.14%	15.35%	36.94%	8.40%	56432	1.48%
		Difference		-4.28%	-3.72%	-4.86%	-0.22%		-0.25%
		t-stat		*-3.90*	*-3.42*	*-3.62*	*-0.01*		*-0.06*
2	0	Extreme Conditions	347	17.84%	13.30%	21.63%	16.76%		
2	0	Normal Conditions	61516	19.39%	11.45%	22.56%	8.03%		
		Difference		-1.55%	1.85%	-0.93%	8.73%		
		t-stat		*-1.91*	*1.39*	*-0.89*	*0.34*		
		Difference-in-Difference		-2.73%	-5.57%	-3.93%	-8.95%		
		t-stat		*-2.29*	*-5.31*	*-2.70*	*-2.75*		
3	1	Extreme Conditions	347	6.17%	3.80%	4.63%	3.76%	310	5.84%
3	1	Normal Conditions	61516	6.22%	3.83%	4.70%	4.15%	53413	8.47%
		Difference		-0.05%	-0.03%	-0.07%	-0.39%		-2.63%
		t-stat		*-0.09*	*-0.06*	*-0.15*	*-0.18*		*-0.76*
3	0	Extreme Conditions	347	42.02%	59.01%	34.05%	53.60%		
3	0	Normal Conditions	61516	29.45%	44.66%	23.37%	36.73%		
		Difference		12.57%	14.35%	10.68%	16.87%		
		t-stat		*11.70*	*6.28*	*8.42*	*0.95*		
		Difference-in-Difference		-12.62%	-14.38%	-10.75%	-17.26%		
		t-stat		*-9.81*	*-13.14*	*-7.29*	*-7.46*		

Table 11 – Informativeness of Algorithmic Trading by Market Conditions – Univariate Analysis

This table presents univariate analysis of the informativeness of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. For buys, price change is measured as the midquote prevailing 5 min (15, 30 or 60 min) after transaction less the buy price, expressed as a ratio of the buy price. For sells, price change is measured as the sell price less the midquote 5 min (15, 30 or 60 min) after order submission, expressed as a ratio of the sell price. *Informativeness* for a trader category during a 5-minte interval is calculated as the volume weighted average of all price changes relating to the trader category during the 5-minutes interval, expressed in basis points. *Algo* is a binary variable that identifies algorithmic messages. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Panel A: 1-Hour Persistence

Market Conditions	Algo	N	Informativeness			
			5 mins	15 mins	30 mins	60 mins
Extreme Conditions	1	347	0.43	-2.10	-2.10	-1.30
	0	347	6.99	8.19	8.21	7.86
		Difference	-6.56	-10.29	-10.31	-9.16
		t-stat	*-0.77*	*-1.22*	*-1.21*	*-1.07*
Normal Conditions	1	62638	1.20	1.49	1.90	2.00
	0	62638	-0.02	-0.20	-0.50	-0.60
		Difference	1.22	1.69	2.40	2.60
		t-stat	*4.00*	*5.44*	*7.67*	*8.08*
Difference-in-Difference			-7.78	-11.98	-12.71	-11.76
t-stat			*-11.19*	*-17.11*	*-17.93*	*-16.51*

Panel B: 30-Minute Persistence

Market Conditions	Algo	N	Informativeness			
			5 mins	15 mins	30 mins	60 mins
Extreme Conditions	1	960	1.58	2.45	3.32	2.65
	0	960	5.62	5.07	4.53	4.93
		Difference	-4.04	-2.62	-1.21	-2.28
		t-stat	*-0.72*	*-0.47*	*-0.22*	*-0.40*
Normal Conditions	1	62022	1.33	1.56	1.94	2.06
	0	62022	-0.20	-0.40	-0.60	-0.70
		Difference	1.53	1.96	2.54	2.76
		t-stat	*2.65*	*3.37*	*4.40*	*4.83*
Difference-in-Difference			-5.57	-4.58	-3.75	-5.04
t-stat			*-6.26*	*-5.14*	*-4.19*	*-5.71*

Panel C: 15-Minute Persistence

Market Conditions	Algo	N	Informativeness			
			5 mins	15 mins	30 mins	60 mins
Extreme Conditions	1	1790	3.76	4.02	4.78	4.19
	0	1790	-2.7	-2.7	-3.1	-2.7
		Difference	6.46	6.72	7.88	6.89
		t-stat	*1.38*	*2.32*	*1.67*	*1.48*
Normal Conditions	1	61192	1.13	1.38	1.76	1.90
	0	61192	0.33	0.10	-0.10	-0.30
		Difference	0.80	1.28	1.86	2.20
		t-stat	*1.47*	*2.32*	*3.36*	*3.88*
Difference-in-Difference			5.66	5.44	6.02	4.69
t-stat			*5.98*	*5.74*	*6.25*	*5.01*

Panel D: 5-Minute Persistence

Market Conditions	Algo	N	Informativeness			
			5 mins	15 mins	30 mins	60 mins
Extreme Conditions	1	5128	1.27	1.52	1.95	1.91
	0	5128	-2.9	-3	-3.2	-3.2
		Difference	4.17	4.52	5.15	5.11
		t-stat	*1.79*	*1.93*	*2.19*	*2.19*
Normal Conditions	1	57854	1.35	1.60	2.00	2.11
	0	57854	0.59	0.36	0.13	0.01
		Difference	0.76	1.24	1.87	2.10
		t-stat	*1.35*	*2.17*	*3.24*	*3.65*
Difference-in-Difference			3.41	3.28	3.28	3.01
t-stat			*3.93*	*3.81*	*3.76*	*3.44*

Table 12 – Informativeness of Algorithmic Trading by Market Conditions – Difference-in-Difference Analysis

This table presents univariate analysis of the informativeness of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. For buys, price change is measured as the midquote prevailing 5 min (15, 30 or 60 min) after transaction less the buy price, expressed as a ratio of the buy price. For sells, price change is measured as the sell price less the midquote 5 min (15, 30 or 60 min) after order submission, expressed as a ratio of the sell price. *Informativeness* for a trader category during a 5-minte interval is calculated as the volume weighted average of all price changes relating to the trader category during the 5-minutes interval, expressed in basis points. Traders classified as Client 1 and Client 3 are both customers of the exchange, but Client 3 traders employ their own Clearing Member –typically, entities that avail such a facility FIIs, Mutual Funds, NRIs, Domestic Body Corporates & Domestic Financial Institutions etc. Client 2 traders are member of the exchange. *Algo* is a binary variable that identifies algorithmic messages. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Market Conditions	Client	Algo	N	Informativeness 5 mins	Informativeness 60 mins
Extreme Conditions	1	1	347	2.22	-2.00
	1	0		3.72	6.79
			Difference	-1.50	-8.79
			t-stat	*-0.42*	*-1.75*
Normal Conditions	1	1	62638	0.90	1.85
	1	0		-1.80	-0.60
			Difference	2.70	2.45
			t-stat	*6.47*	*5.23*
Difference-in-Difference				-4.20	-11.24
t-stat				*-8.65*	*-19.17*
Extreme Conditions	3	1	347	-0.70	-2.10
	3	0		-1.90	-1.30
			Difference	1.20	-0.80
			t-stat	*0.56*	*-0.25*
Normal Conditions	3	1	62638	-0.40	-2.00
	3	0		-1.10	-2.40
			Difference	0.70	0.40
			t-stat	*0.76*	*0.46*
Difference-in-Difference				0.50	-1.20
t-stat				*0.59*	*-1.34*
Extreme Conditions	2	1	347	-3.20	-3.30
	2	0		-3.70	-5.90
			Difference	0.50	2.60
			t-stat	*0.34*	*1.02*
Normal Conditions	2	1	62638	-0.20	-0.30
	2	0		2.16	0.62
			Difference	-2.36	-0.92
			t-stat	*-2.41*	*-0.89*
Difference-in-Difference				2.86	3.52
t-stat				*2.88*	*3.33*

Table 13 – Probability of Extreme events and Algorithmic trading

This table presents estimates from Logit models of extreme events. A 5-minute interval is classified as *Extreme* event when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. *Open* is a binary variable equal one during the first hour of trading. *Close* is a binary variable equal one during the last hour of trading. All variables are standardized by stock and calculated using the previous hour's data. The analysis is conducted using data from May, 2012. Two tailed *p-values* are also reported.

	1	2	3	4	5	6
A	-5.38	-5.83	-8.60	-5.26	-5.81	-8.57
	<0.01	*<0.01*	*<0.01*	*<0.01*	*<0.01*	*<0.01*
Participation	-0.91	-0.62	-0.33			
	<0.01	*<0.01*	*0.01*			
Liquidity Provision				-0.54	-0.57	-0.36
				<0.01	*<0.01*	*0.01*
Volatility			3.53			3.53
			<0.01			*<0.01*
Spreads			2.66			2.66
			<0.01			*<0.01*
Abs OIB			1.23			1.18
			<0.01			*<0.01*
Return		-0.36	-0.12		-0.38	-0.12
		<0.01	*0.21*		*<0.01*	*0.19*
Volume		1.06	0.31		1.09	0.32
		<0.01	*<0.01*		*<0.01*	*<0.01*
Close		0.45	0.50		0.49	0.51
		<0.01	*<0.01*		*<0.01*	*<0.01*
Open		-0.73	-0.05		-0.77	-0.06
		<0.01	*0.59*		*<0.01*	*0.46*
Likelihood Ratio	*<0.01*	*<0.01*	*<0.01*	*<0.01*	*<0.01*	*<0.01*
# Observations	62985	62985	62985	62985	62985	62985

Table 14 – Algorithmic Trading by Market Conditions – Contagion Analysis

This table presents contagion analysis of algorithmic trades during periods of market stress- periods when market conditions (Eg: *Volatility* or *Abs OIB*) are abnormally high (greater than 2 std. deviations) for prolonged period of time. For example, a 5-minute period is classified as *Volatility High* when the 5-minute *Volatility* over the past 1 hour has been greater than twice its standard deviation over the sample period. A 5-minute interval is classified as *Extreme* when either *Volatility* or *Spreads* or *Absolute OIB* over the past 1 hour has been greater than twice its standard deviation calculated over the sample period. A 5-minute interval, for stock *i*, is classified as *Extreme-Contagion* when any stock *j* <> *i* has an *Extreme* events during the same 5-minute interval, but stock *i* does not. *Volatility High-Contagion, Spreads High-Contagion and OIB High-Contagion* are defined similarly. *Algo* is a binary variable that identifies algorithmic messages. *Participation* is the proportion of trading volume that involved an Algorithmic trader either on the buy or the sell side. *Liquidity Provision* is the proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on the aggressiveness of the orders involved in the trade. The analysis is conducted using data from May, 2012. *t*-statistics are also reported.

Market Conditions	N	Participation	Liquidity Provision
Extreme-Contagion	10218	35.42%	15.40%
Normal Conditions	52767	38.23%	16.19%
Difference		-2.81%	-0.79%
t-stat		*-13.57*	*-6.77*
Volatility High-Contagion	6894	36.55%	15.79%
Volatility Otherwise	56091	37.92%	16.10%
Difference		-1.37%	-0.31%
t-stat		*-5.63*	*-2.25*
Spreads High-Contagion	3812	33.19%	14.62%
Spreads Otherwise	59173	38.07%	16.16%
Difference		-4.88%	-1.54%
t-stat		*-15.29*	*-8.52*
OIB High-Contagion	152	33.75%	13.65%
OIB Otherwise	62833	37.78%	16.07%
Difference		-4.03%	-2.42%
t-stat		*-2.59*	*-2.75*