Man vs. Machine: Liquidity Provision and Market Fragility

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Emerging Markets Finance Conference, 2015

Background and Motivation

- Equity markets are now largely order matching markets.
  - 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.

- An important concern of exchanges and regulators is to ensure consistent and continual availability of standing limit orders to execute against – in good times and bad.
  - This concern is now focused on Algo traders because of the significant and increasing proportion of liquidity being supplied by them.

Background and Motivation

- In this paper, we investigate the participation and transactional liquidity provided by (voluntary) Algo traders, relative to (voluntary) human traders, during periods of market turbulence or stress, relative to what they do in "normal" periods, and the resultant implications for the fragility of these markets.
  - What is the propensity to stop providing liquidity when the going gets tough?

- We use data from the NSE – a market in which liquidity has always come from voluntary liquidity suppliers, and a market that has always been an electronic order-matching market.

What do we Expect?

- Algo traders should arguably have a competitive advantage over humans during periods of high levels of information intensity or asymmetry or uncertainty.
  - They have an obvious speed advantage.
    - Biais, Foucault, and Moinas (RFS 2010) show how humans face adverse selection costs relative to Algo traders.
  - They are not constrained by limits to human cognition and bounds of human rationality in accessing and processing data across fragmented markets and across related assets, and then trading on it. (Biais and Wooley, WP 2011).

What do we Expect?

- Consistent with an Algo informational advantage, Brogaard (2010) and Hendershott and Riordan (JFQA 2013) find that Algos lead with respect to price discovery, and impound more information than human orders.
- However, their analyses, and all related analyses, span only "normal" periods.
- If it is indeed true that Algos enjoy a competitive advantage over humans specifically in turbulent times, then it is the human rather than the Algo liquidity suppliers that should be the ones withdrawing from the market in tough times.

Reasons for Withdrawal by Algos: Complexity

- "Data" or hard news releases are not "information" – they have to be "processed" into usable information.
  - Algos have an advantage when processing involves only hard data, and the relatively exact sciences.
  - Processing data into information in the economic world is complex, imperfect, subjective, uncertain, and involves "soft" analyses. Hence, traders face "preference uncertainty", modeled specifically in this context by Biais, Hombert, and Weill (JES 2014).
  - Can Algos be pre-programmed to address the entire spectrum of preference uncertainties and complexities?
    - Buenzi (Foresight 2011) suggests otherwise.

Reasons for Withdrawal by Algos: Complexity

- Speed – which is what enables Algos to exploit price distortions before human traders can – also limits the time available for processing information: Dugast and Foucault (2014) theorize that such constrained information processing would increase the incidence of 'mini-flash crashes' as in the 'twitter crash' of April, 2013.
- Periods of market stress are rare and unique, and can pose severe challenges to algos whose decisions are based on pre-programmed routines with parameters set ex ante.
- Algos also adapt continually and further reduces the benefits of applying rules based on past lessons.

Reasons for Withdrawal by Algos: Complexity

- Risks of serious glitches while running new or adapting old algorithms are high: for example, Knight Capital.
- Consequently, Algo traders 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*" (Yadav, 2014).
- In turbulent conditions, automated risk management algorithms might reduce participation and liquidity provision (Zigrand, Cliff and Hendershott, 2011); or simply apply the "kill switch" (Buenza, et al., 2011).

Reasons for Withdrawal by Algos: Complexity

- Algos should lose their informational advantage over humans during extreme events/periods of market stress.

"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).

Formal Studies?

Vernon Smith (1962); Das et al. (2001); De Luca et al. (2011).

We test this in terms of impact.

Reasons for Withdrawal by Algos: Short Horizon and Limited Capital

- Long horizon hinders the Algo advantage of trading in and out faster than others (Javanovic and Menkveld, 2010)
  - Such agility is hindered when capital is locked-up.
  - Algos 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.
  - 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.

Reasons for Withdrawal by Algos: Correlated Order Flows

- Chaboud, Chiquoine, Hjalmarsson, and Vega (JF, 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*".
- They also 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.*"

- Laube and Malcenieks (2013) find that HFT increases the commonality in returns and in liquidity.

Reasons for Withdrawal by Algos: Correlated Order Flows

- *"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"*
  - (Zigrand, Shin, and Buenza, 2011).

- The official CFTC/SEC report on the "Flash Crash" also discusses the destabilizing feedback effect of "hot-potato" or "pass-the-parcel" behavior generated by holding of small positions for short periods.
  - The large volume of trading among algorithms triggered other algorithms that sold aggressively in high volume markets.

Reasons for Withdrawal by Algos: Decoupling from Fundamental Value

- Zigrand, Shin and Beunza (2011) argue the propensity for this is greater in markets dominated by Algos, and this can be destabilizing: "***Some algorithms know the price of everything and the value of nothing***…. *market dynamics dominated by very short horizon robots run the risk of being "freer" in the sense of being more decoupled from a fundamental anchor, such as the fundamental valuation of payoffs and earnings. Markets that are more decoupled from fundamentals can depart more readily and be pushed further by self-reinforcing [destabilizing] feedbacks."*

Extensive Regulatory Concerns

- *Algos improves overall liquidity, it also generates greater dangers of periodic episodic illiquidity*
  - UK Foresight Report

- *"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….."*
  - Mary Schapiro, Then Chairman of SEC

Extensive Regulatory Concerns

Andrew Haldane, Executive Director for Financial Stability at the Bank of England, in ‘Race to Zero’ (July, 2011):

“*HFT liquidity, evident in sharply lower peacetime bid-ask spreads, may be illusory. In wartime, it disappears. This disappearing act, and the resulting liquidity void, is widely believed to amplified the price discontinuities evident during the Flash Crash. HFT liquidity proved fickle under stress, as flood turned to drought*”

Extensive Regulatory Concerns

- Regulatory concerns are also highlighted by proposals aimed at constraining Algos:
  - There has been a proposal (House Resolution 1068) to impose a per-trade tax of .25%.
    - EU has proposed a similar tax.
  - Some have suggested implementing fees when the number of canceled orders by a market participant exceeds a certain level, or limit the number of canceled orders.
  - Others have recommended requiring quotes to have a minimum life before they can be canceled or revised.

This Paper

- Extant empirical research has largely focused only on “normal” market conditions.
- Our contribution 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 Algo participation in trades and liquidity provision is as reliable and stable as that of humans even in times of market stress.
- Or whether complexity, short horizon, and correlation in trading results in Algos being just “fair weather” liquidity suppliers.

Salient Results

- Buy-side algorithmic traders significantly reduce their participation and liquidity provision during periods of market stress
- Analyzed in a few different ways:
  1. Simple Univariate: Algo in Normal conditions vs. Stressful conditions.
  2. Difference-in-Difference, 2012: Comparing the change in participation and liquidity provision during stressful conditions between algo and manual traders of the same category; entire analysis based on 2012 data. Also examine the change in limit order book participation and pricing
  3. Difference-in-Difference, 2012 vs 2006: Similar to the previous analysis, except that the control group consists of same-category traders from 2006 – pre-automation era.
  4. Multivariate version of 2 and 3: with controls.

Salient Results

- Buy-side Algo traders behave differently from sell-side Algo traders.
  - Sell-side Algos, although also voluntary traders, appear to have reputational or contractual considerations.

- This change in trading behavior corresponds one-to-one with the change in informational advantage of different Algo categories
  - Buy Side Trader category 1 Algos suffer the most in terms of informational advantage during stressful times – supporting the complexity hypothesis.
  - Sell side Trader Algos suffer the least.

Salient Results

- 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.
  - reduction in AT trades (relative to MT) because AT's withdraw from the order book and because AT's orders reflect a higher price for liquidity supply services.

Salient Results

- Withdrawal of Algos, in terms of participation and liquidity provision, significantly increases the probability of an *Extreme* event in the next 5-min interval.
  - This is where market fragility comes in.
    - This result holds even after controlling for the in-built persistence of *Extreme* events.

- Finally, we find that Algos withdraw significantly even when any of the other stocks in the Nifty 50 has experienced an *Extreme* event
  - Withdrawal of Algo trading is correlated across stocks – even when stressful market conditions are not

Data

- Trades and Orders data, with an ‘Algo’ indicator and trader classifications.
- Trader Categories: Client 1,2 and 3
  - 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.
- Time period: May 2006 and May 2012
- Stocks: Nifty 50
- Trading Hours: 9 to 3.30 pm

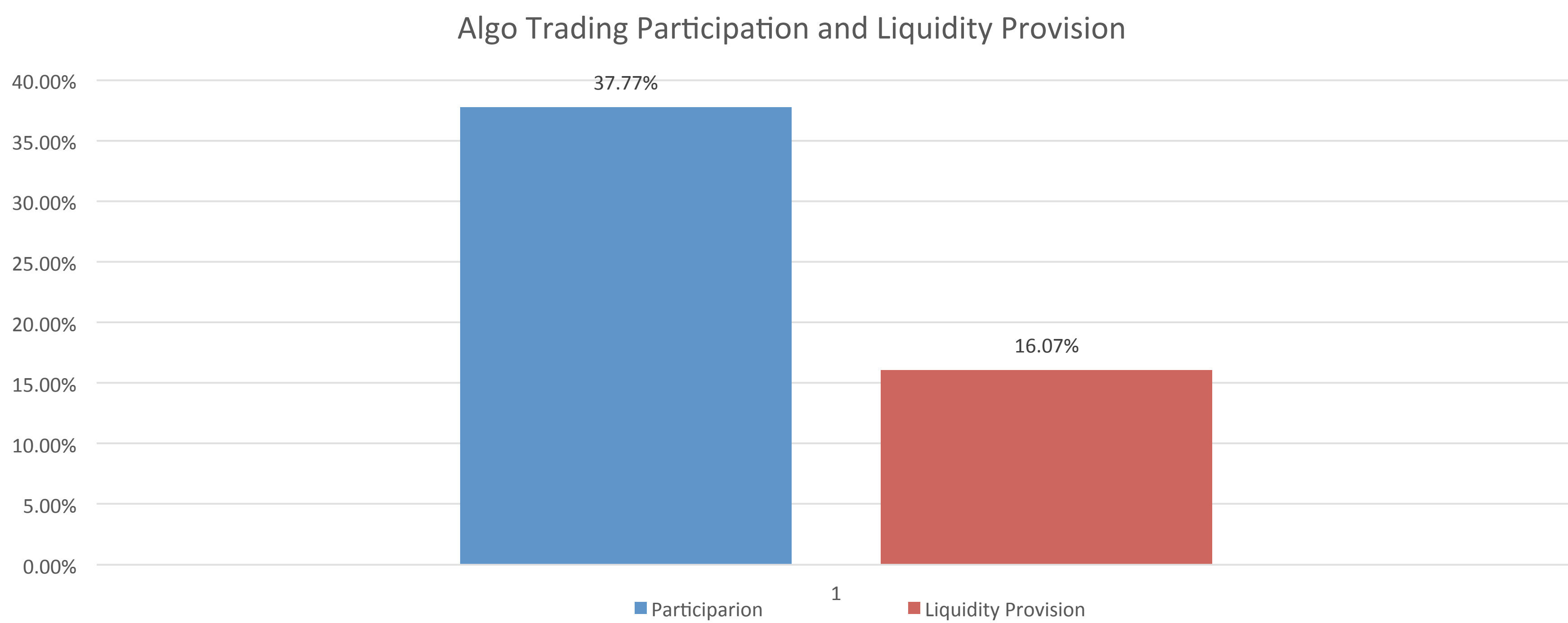
Methodology Overview

- We study Algos' trading and liquidity provision in normal times and in extreme periods.

- We examine Algos' trading with two variables:
  - Participation
    - proportion of trading volume that involves an Algorithmic trader either on the buy or the sell side.
  - Liquidity Provision
    - proportion of trading volume for which algorithmic traders provided liquidity, which is calculated based on whether they were posting a standing limit order that got picked in the trade.

Algo Participation and Liquidity Provision

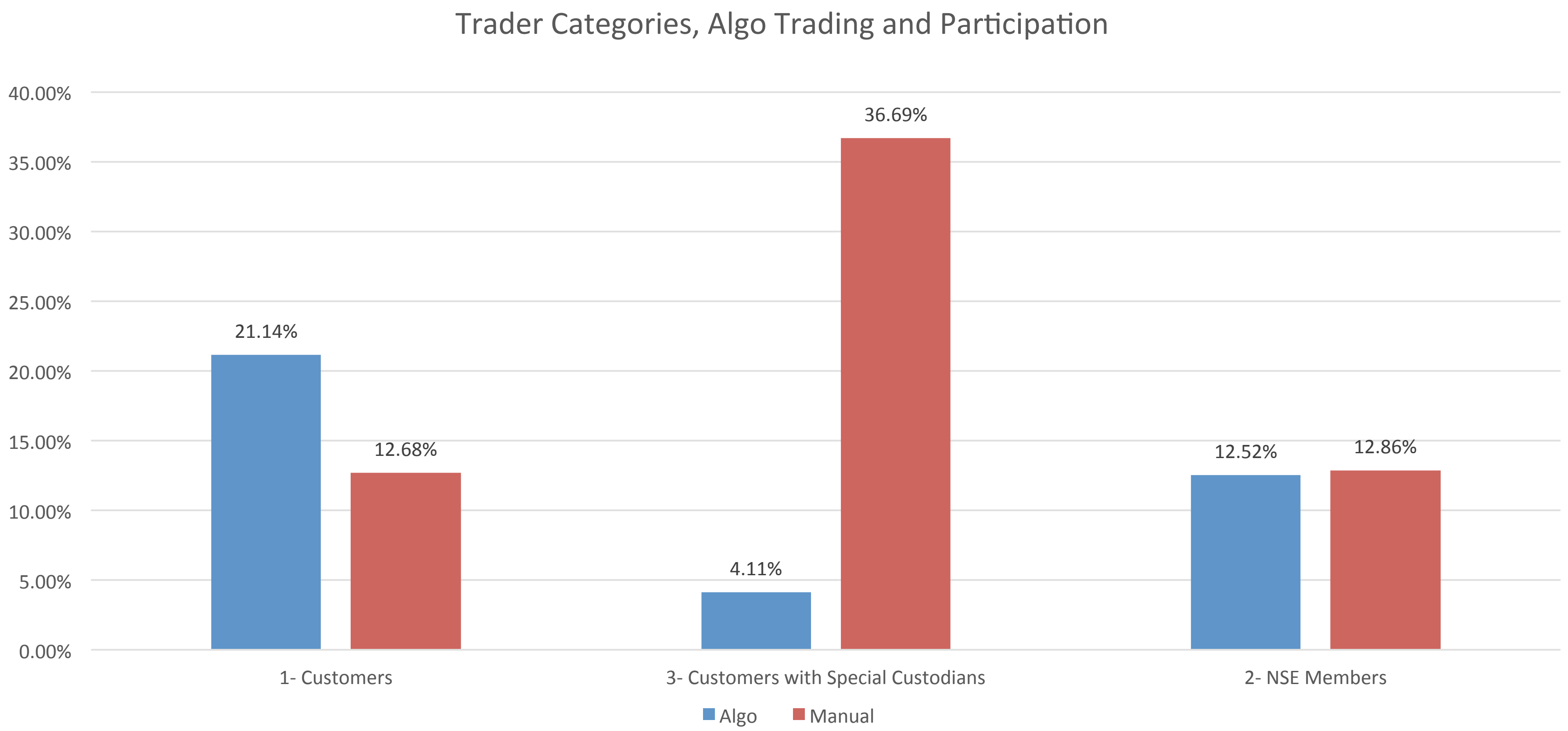
- On average, in May 2012, there are 454 trades and 28594 number of shares traded in a 5 minute interval.



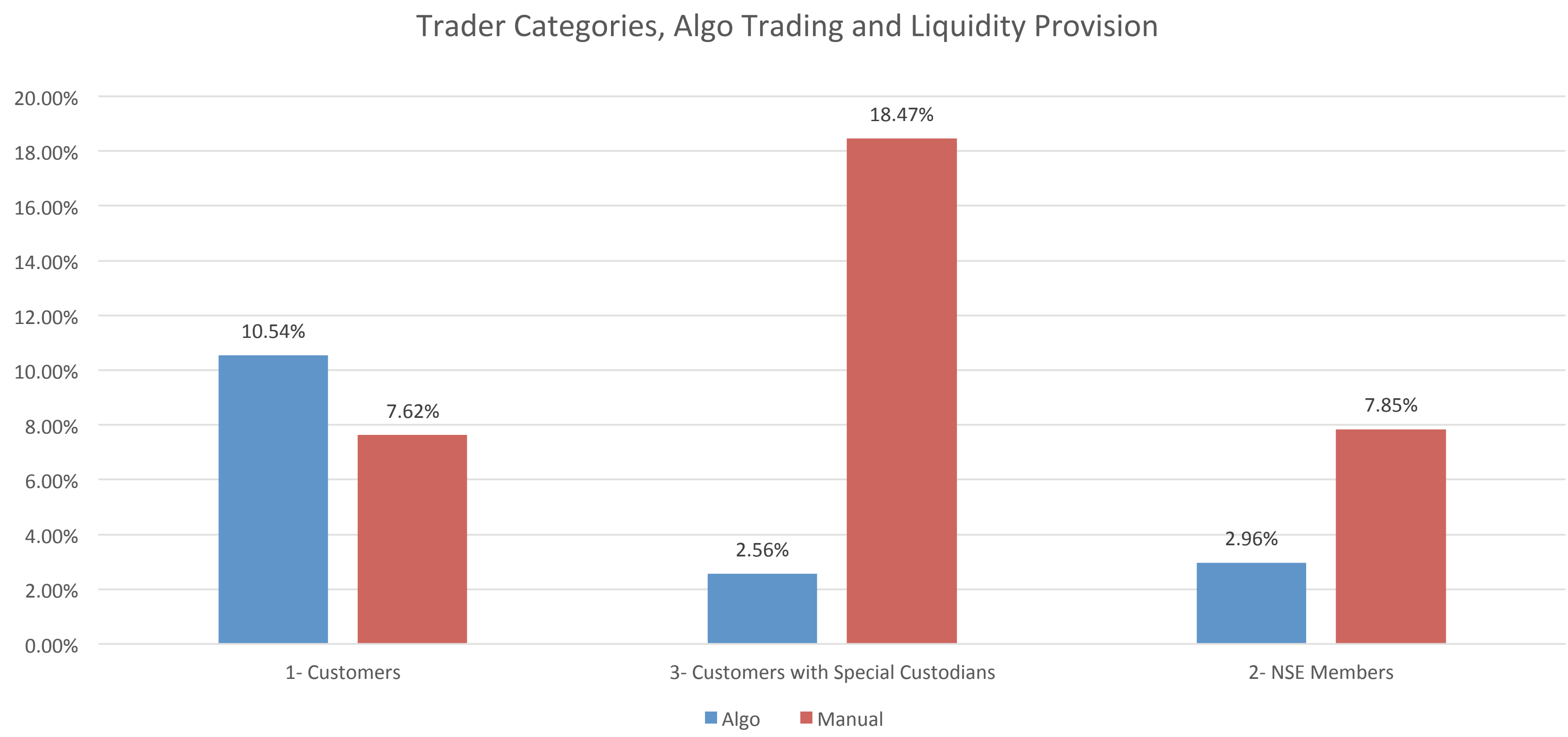
Algos account for 38% of the trading volume, and provide liquidity in 16% of trading volume on each side of the book.

Algo vs. Manual
Different Trader Categories

- Client 3 are mostly manual traders, Client 2 roughly half, and Client 1 mainly Algo traders.



Algo Participation and Liquidity Provision



Methodology Overview

- Extreme periods of market stress are when Volatility, Spreads or Absolute Order Imbalance are abnormally high for prolonged period of time.

- Extreme Period:
  - A 5-minute interval is classified as *Extreme* when the 5-minute *Volatility,* and/or the 5-minute *Spread,* and/or the 5-minute *Absolute Order Imbalance* over the past one hour has, on average, been greater than two standard deviations from the mean.
    - 5% chance of a greater than two standard deviations for one interval.
    - On average, greater than two STDs over 12 successive intervals is persistent stress and our Extreme event
    - Genuinely a rare occasion

Methodology Overview

- We also use the trader category provided in the dataset to conduct a Difference-in-Difference analysis to infer the effect of automation in extreme market conditions
- Comparison of Algo trading activity in periods of market 'stress' and normalcy after controlling for type of trader
- Client 1 Algo Trader provides x1% liquidity during normal times and x2% in extreme conditions
- Client 1 Manual Trader provides y1% liquidity during normal times and y2% in extreme conditions
- Effect of Automation on liquidity provision in extreme conditions

  = (x1% - x2%)-(y1%-y2%)

Univariate Analysis

- Overall Algo participation and liquidity provision drops about 25% for all types of extreme conditions

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*

Analysis across Different Trader Categories

- A natural follow-up question is: don't all voluntary traders withdraw during periods of market stress?
- Hence, in our next analysis, we compare Algos with two groups voluntary traders
  - Manual (voluntary) traders of 2012 of the same trader-category – Table 4A
  - Manual (All) traders of 2006 of the same trader-category – Table 4B
- The difference-in-difference analysis of trading participation and liquidity provision provides a more robust understanding of incremental influence of automation on trading strategies.

Analysis across Different Trader Categories

- Table 4a: Difference-in-Difference analysis with contemporaneous manual traders of the same trader-category as a control group.
- Results largely confirm the earlier finding – algorithmic traders withdraw significantly more than their manual peers during periods of market stress!
- However, significant difference between buy-side and sell-side Algo trading
  - Buy-side (Client 1 and 3) withdraw significantly more
  - Sell-side (Client 2) no significant change in trading activity
  - Reputation a factor for sell-side Algos?

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*

Analysis across Different Trader Categories

- Table 4b: Difference-in-Difference analysis with manual traders of 2006 of the same trader-category as the control group.
- Results are qualitatively similar.
- Category 1 algorithmic traders withdraw liquidity the most during periods of market stress and category 2 algorithmic traders withdraw the least.
- Interestingly, Category 1 traders in 2006 increase their Participation and Liquidity Provision during Extreme events.
- However, even manual traders in 2012 withdraw during periods of stress.

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*

Multivariate Analysis

- Table 5 Multivariate results further confirm the univariate results

- Algo *Liquidity Provision* drop significantly in *Extreme* conditions after all controls.

- Volatility
  – Participation decreases with Volatility
  – But increases with Volatility when it is *High*
  – The increased participation appears to be a liquidity demanding since Algo liquidity provision drops significantly when Volatility is *High*

Multivariate Analysis

- Spreads
  - Algo participation is only related to Spreads when they are very large – and the relation is negative and significant.
  - Algo liquidity provision is positively related to Spreads, but the relation is reversed when Spreads are very large
    - Algo turn from liquidity providers to liquidity demanders when the demand for liquidity is very high.

- Absolute OIB
  - Participation and Liquidity provision are negatively related to Abs OIB - even a moderate increase is negatively related!
  - To the extent Abs OIB is a proxy for informed order flow, Algo appear to be extremely sensitive to toxic order flow.

	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

Multivariate Analysis

- Table 6
- Similar analysis as Table 5, except that the dependent variables are not *Participation* and *Liquidity Provision,* but Δ*Participation* and Δ *Liquidity Provision*
- Δ *Liquidity Provision* (Δ*Participation*) is the difference between *Liquidity Provision* (*Participation*) of algorithmic and manual traders of the same client category in a 5-min interval
- Multivariate results further confirm the univariate results

	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%

Limit order activity of algorithmic traders and market conditions

- Is the reduction in algorithmic trades during extreme conditions because of their withdrawal from the order book?
- Or is it due to algorithmic traders posting relatively more passive orders?
- Withdrawal from liquidity provision or an increase in cost of liquidity provision?

Limit order activity of algorithmic traders and market conditions

- 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.

- Change in cost of liquidity provision is measured as the change in the relative pricing or aggressiveness of the new algorithmic and manual orders that are actually submitted during periods of market stress

Limit order activity of algorithmic traders and market conditions

- Proportion of Algo new orders and net new orders (both number and volume) drop significantly during extreme market conditions
- But overall no significant change in pricing aggressiveness

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*

Limit order activity of algorithmic traders and market conditions

- Next, we repeat the analysis using a difference-in-difference approach

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*		

Limit order activity of algorithmic traders and market conditions

- All categories of AT withdraw significantly more than their MT counterparts.
- First, 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.

Limit order activity of algorithmic traders and market conditions

- Analysis of change in pricing aggressiveness is much more conclusive than with the lower power overall analyses reported earlier
- 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.

- All categories of voluntary automated traders withdraw from the order book significantly more than their manual peers during stressful market conditions.
- And with the exception of exchange members, also place orders that are significantly less aggressive than the orders of the corresponding group of manual traders.

Bottom Line

- In summary, Algos withdraw trading and liquidity during periods of market stress!
- But why do they do so?
  - Complexity
  - (Very, very) Short horizon
  - Exacerbated by correlated trade flows
  - Fundamental value de-coupling

Univariate Analysis

- Persistence of disturbances is really an important factor
- Withdrawal of Algo trading and liquidity provision almost linearly increases with the persistence of market stress.
- Consistent with complexity driven withdrawal rather than short-horizon related withdrawal.

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*

Informativeness of Algos and Market Conditions

- Table 7
- *Informativeness* for a trader category during a 5-minute interval is calculated as the volume weighted average of all price changes relating to the trader category during the 5-minutes 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 of Algos and Market Conditions

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***

Results show that Algos, who are significantly more informed in Normal Conditions, lose their competitive advantage during extreme conditions.

Manual traders are significantly more informed during extreme market conditions.

This evidence is entirely consistent with the Complexity hypothesis – Algos struggle to react to unfamiliar conditions

Informativeness of Algos and Market Conditions – Different Trader Categories

- Next we conduct a similar analysis of Algo informativeness, but we employ a difference-in-difference approach for different trader categories
  - Controlling for different trader types, we examine the changing informativeness of Algos in periods of market stress.

- The results further support the Complexity hypothesis.

Market Conditions	Client	Algo	N	Informativeness	
				5 mins	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*

Informativeness of Algos and Market Conditions – Different Trader Categories

- More importantly, the results also show that while Client 1 Algos lose the most during extreme conditions and Client 2 Algos perform the best.

- That the change in informativeness and change in participation and liquidity provision of Algos correspond strongly further supports that complexity story.
  - Algos exit of markets during periods of market stress is associated with the loss of their informational competitive advantage.

Fragility: Probability of Extreme events and Algo trading

- Having seen that Algos withdraw *Participation* and *Liquidity Provision* in extreme conditions, we ask if withdrawal in turn further increases the probability of observing an extreme event in the next 5-minute interval.

- This questions speaks directly to the issue of market fragility
  - A vicious circle of Algo withdrawal and extreme events would quickly destabilize markets

Probability of Extreme events and Algo trading

- Table 9
- Logit models are used to explain the probability of observing an extreme event in the next 5-minute interval as a function of Algo *Participation* and *Liquidity Provision* and other pertinent variables.

- Results show that, across the board, Algo withdrawal from trading and/or liquidity provision significantly increases the probability of observing an extreme event

Probability of Extreme events and Algo trading

- Of course, extreme is persistent by design, hence we also control for prevailing market conditions – Volatility, Spreads, Abs OIB, Volume and Returns

- Our results show that even after controlling for the persistent nature of extreme market conditions, Algo 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%
  - A one standard deviation decrease in *Liquidity Provision* increases the odds of an extreme event by at least 30%

	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

Algorithmic Trading by Market Conditions – Contagion Analysis

- An unique feature of Automated traders is that because their monitoring costs are negligible compared to manual traders, they can have a simultaneous presence in multiple securities.
- Hence, does the previously discussed withdrawal by algorithmic traders during *Extreme* events have repercussions for liquidity of other stocks?
- Such an analysis of market contagion also speaks to the issue of market fragility

Algorithmic Trading by Market Conditions – Contagion Analysis

- A 5-minute interval, for stock *i*, is classified as *Extreme-Contagion* when any stock *j* <> *i* has an *Extreme* event during the same 5-minute interval, but stock *i* does not.
- *Volatility High-Contagion, Spreads High-Contagion and OIB High-Contagion* are defined similarly.
- We find that algo participation and liquidity provision drops significantly for all types of extreme conditions.

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*

Limitations

- Future Versions will try to address several issues:
  - Tease out more carefully other reasons for withdrawal: short horizon, correlated trading, and fundamental value decoupling.
  - Smarter econometrics to control for endogeniety.
  - Integration of futures markets.
  - Direct testing of other measures focusing on the order-book.

Salient Results

- Algorithmic traders significantly reduce their participation and liquidity provision during periods of market stress.

- Buy-side Algo traders (Categories 1 and 3) behave differently from sell-side (Category 2) Algo traders.
  - Sell-side either don't withdraw or increase participation, but buy-side invariably withdraw
  - Sell-side Algos, although voluntary traders, appear to have a reputational cost to consider before pulling out during stressful conditions

Salient Results

- This change in trading behavior corresponds one-to-one with the change in informational advantage of different Algo categories
  - Trader category 1 Algos suffer the most in terms of informational advantage during stressful times – supporting complexity hypothesis.
  - Trader category 2 Algos suffer the least

- Withdrawal of Algos, in terms of participation and liquidity provision, significantly increases the probability of an *Extreme* event in the next 5-min interval.
  - This is where market fragility comes in.
    - This result holds even after controlling for the in-built persistence of *Extreme* events.

Salient Results

- Finally, we find that Algos withdraw significantly even when any of the other stocks in the Nifty 50 has experienced an *Extreme* event
  - Withdrawal of Algo trading is correlated across stocks – even when stressful market conditions are not