Low-Frequency Traders in a High-Frequency world: A Survival Guide

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Key Points

- Multiple empirical studies have shown that Order Flow Imbalance has explanatory power over the trading range.
- The PIN Theory (Easley et al. [1996]) reveals the Microstructure mechanism by which
  - Market Makers adjust their trading range to avoid being adversely selected by Informed Traders.
  - Informed Traders reveal their future trading intentions when they alter the Order Flow.
  - Consequently, Market Makers' trading range is a function of the Order Flow imbalance.
- **VPIN is a High Frequency estimate of PIN, which can be used to detect the presence of Informed Traders.**

SECTION I
The great divide

Is speed the real issue?

- Faster traders are nothing new:
  - Nathan Rothschild is said to have used racing pigeons to trade in advance on the news of Napoleon's defeat at Waterloo.
  - Beginning in 1850s, only a limited number of investors had access to telegraphy.
  - The telephone (1875), radio (1915), and more recently screen trading (1986) offered speed advantages to some participants over others.
  - Leinweber [2009] relates many instances in which technological breakthroughs have been used to most investors' disadvantage. ***So … what is new this time?***

A change in paradigm

- High Frequency Trading (HFT) is not Low Frequency Trading (LFT) on steroids.
- HFT have been mischaracterized as ‘*cheetah-traders*’.
- Rather than speed, the true great divide is a “change in the trading paradigm”.
- HFT are strategic traders. In some instances, they:
  - act upon the information revealed by LFT’s actions.
  - engage in sequential games.
  - behave like predators.
- Speed is an advantage, but there is more to it…

What is the new paradigm? (1/3)

- Time is a measuring system used to sequence observations.
- Since the dawn of time, humans have based their time measurements in chronology: Years, months, days, hours, minutes, seconds, and since recently milliseconds, microseconds ...
- This is a rather arbitrary time system, due to the key role played by the Sun in agricultural societies.

What is the new paradigm? (2/3)

- Machines operate on an internal clock that is not *chrono* based, but *event* based: The cycle.
- A machine will complete a cycle at various chrono rates, depending on the amount of information involved in a particular instruction.
- As it happens, HFT relies on machines, thus measuring time in terms of events.
- Thinking in volume-time is challenging for us humans. But for a ‘silicon trader’, it is the natural way to process information and engage in sequential, strategic trading.

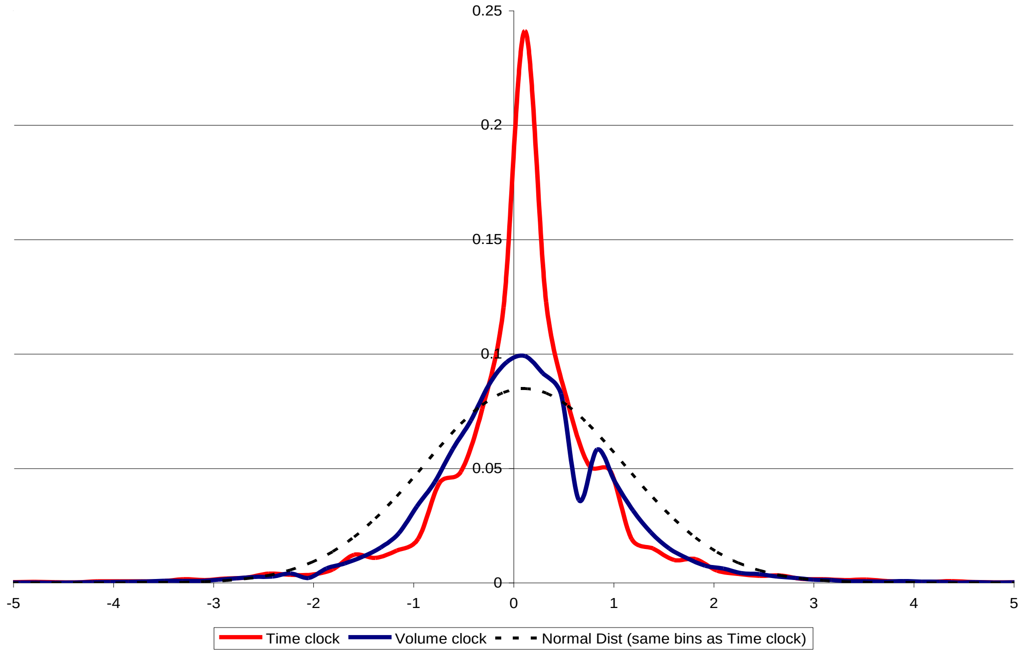
What is the new paradigm? (3/3)

- The new paradigm is "***event-based time***". The simplest example is dividing the session in equal volume buckets. This transformation removes most intra-session seasonal effects.
- For example, HF market makers may target to turn their portfolio every fixed number of contracts traded (volume bucket), regardless of the chrono time.
- In fact, working in volume time presents significant statistical advantages.

Volume time vs. Chrono time

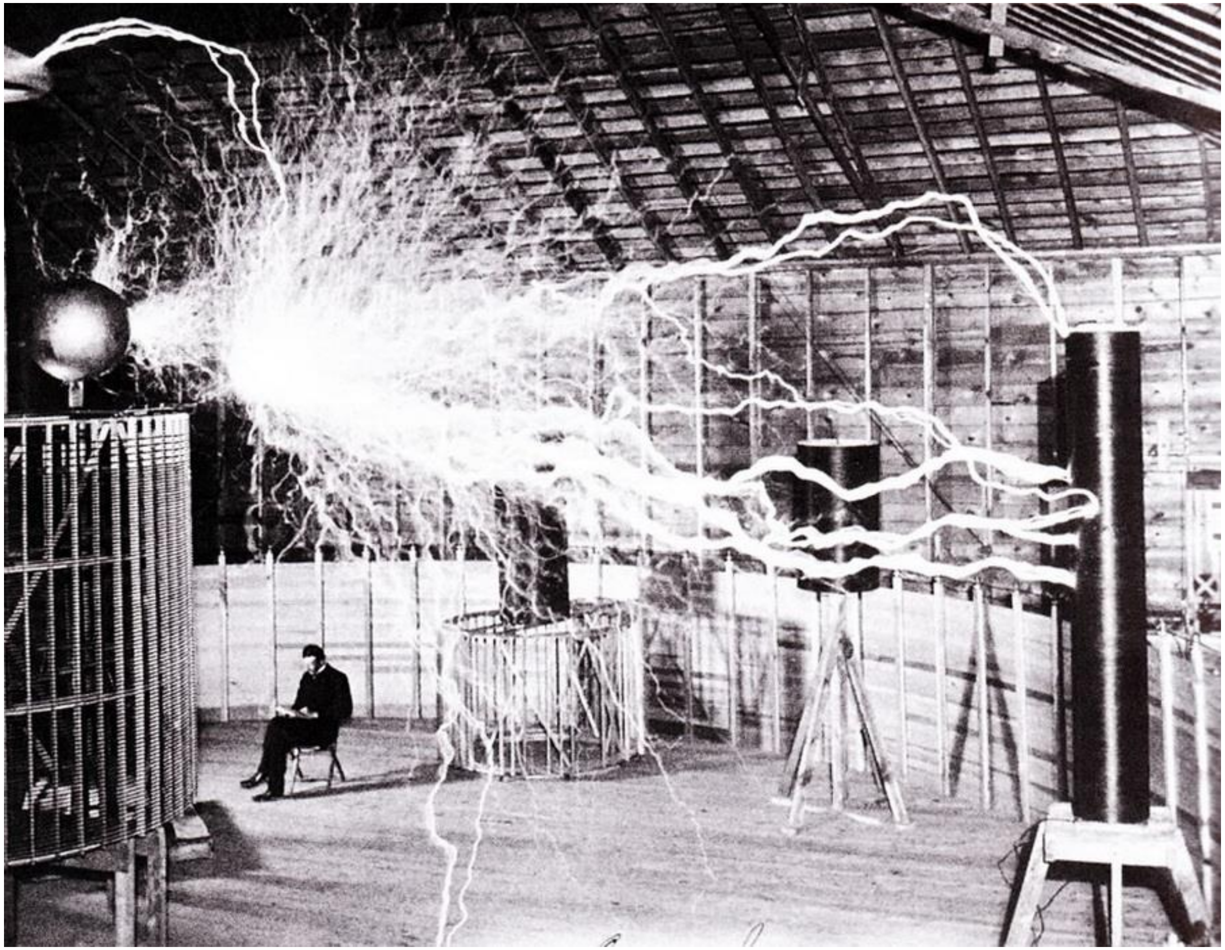
Stats (50)	Chrono time	Volume time
Mean	0.0000	0.0000
StDev	1.0000	1.0000
Skew	-0.0788	-0.2451
Kurt	31.7060	15.8957
Min	-21.8589	-20.6117
Max	19.3092	13.8079
L-B*	34.4551	22.7802
White*	0.0971	0.0548
J-B*	34.3359	6.9392

Stats (100)	Chrono time	Volume time
Mean	0.0000	0.0000
StDev	1.0000	1.0000
Skew	-0.1606	-0.4808
Kurt	44.6755	23.8651
Min	-28.3796	-29.2058
Max	24.6700	15.5882
L-B*	115.3207	36.1189
White*	0.0873	0.0370
J-B*	72.3729	18.1782



Sampling by Volume time allows for a partial recovery of Normality, IID

SECTION II
High Frequency and Adverse Selection



Little known species you should be aware of

- **Predatory algorithms** are a special kind of informed traders. Rather than possessing exogenous information yet to be incorporated in the market price, they know that their endogenous actions are likely to trigger a microstructure mechanism, with foreseeable outcome. Examples include:
  - Quote stuffing: Overwhelming an exchange with messages, with the sole intention of slowing down competing algorithms.
  - Quote dangling: Sending quotes that force a squeezed trader to chase a price against her interests.
  - Pack hunting: Predators hunting independently become aware of each others activities, and form a pack in order to maximize the chances of triggering a cascading effect.

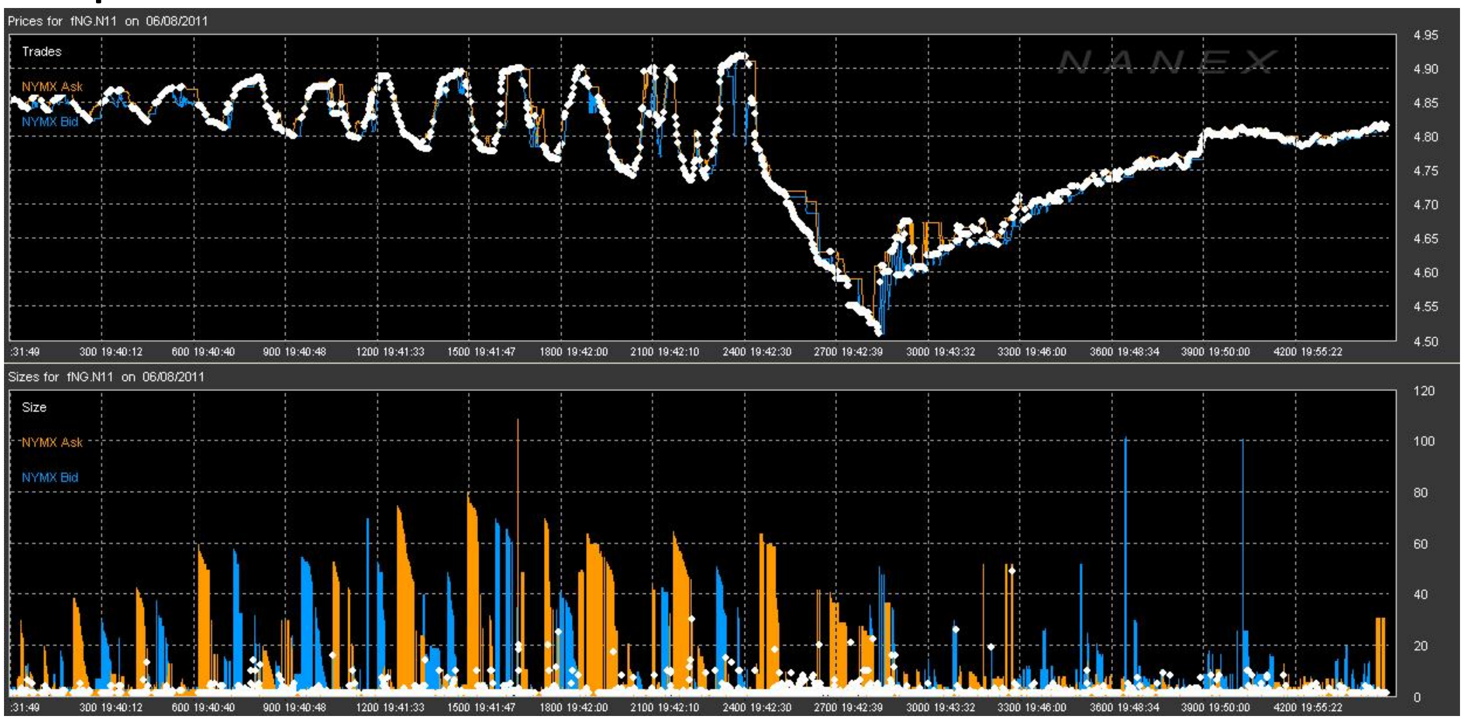
Slow chess may be harder than you think (1/2)

- O'Hara [2011] presents evidence of their disruptive activities.

- A quote dangler forcing a desperate trader to chase a price up. As soon as the trader gives up, the dangler quotes back at the original level, and waits for the next victim.

Slow chess may be harder than you think (2/2)

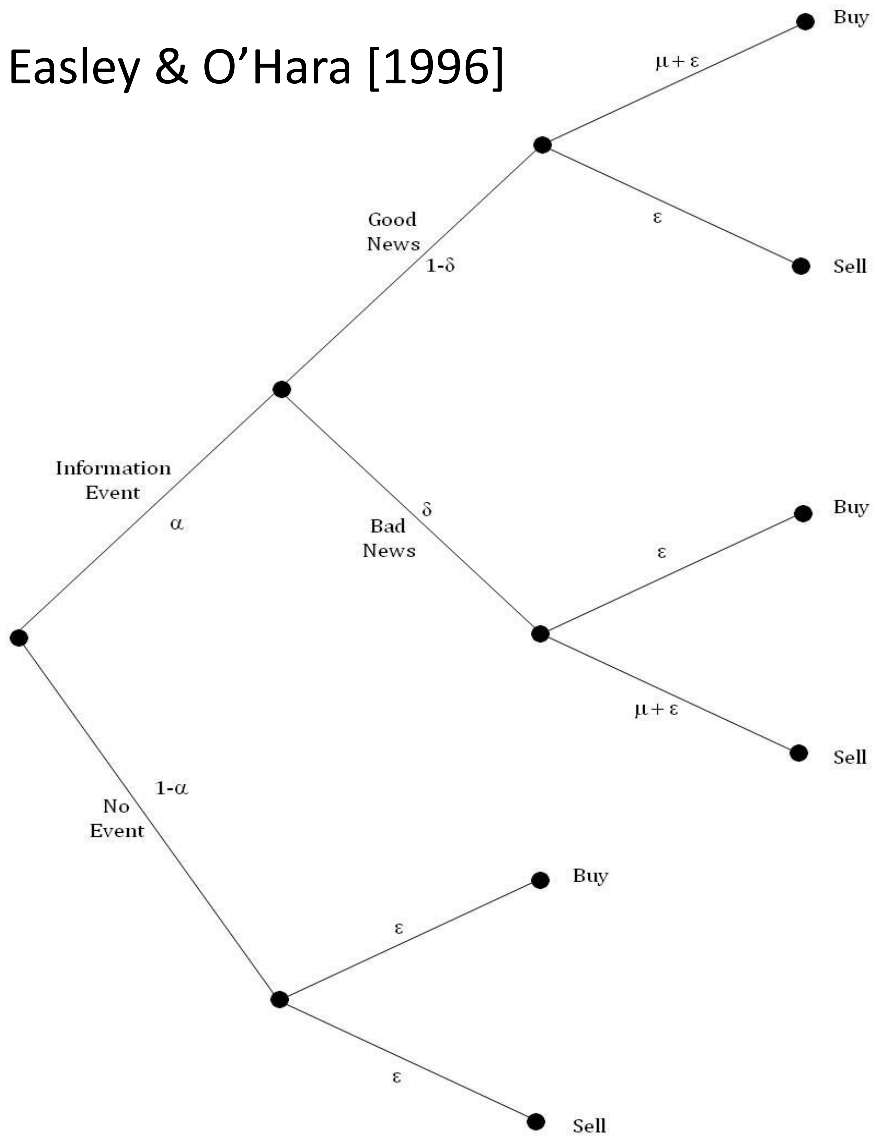
- NANEX [2011] shows what appears to be pack hunters forcing a stop loss.



- Speed makes HFTs more effective, but slowing them down won’t change their basic behavior: ***Strategic sequential trading***.

The PIN Theory

Easley & O'Hara [1996]



PIN estimates the probability that market makers are being adversely selected (i.e., provide liquidity to an informed trader).

$$E[S_i \mid t] = P_n(t)S_i^* + P_b(t)\underline{S}_i + P_g(t)\overline{S}_i$$

$$B(t) = E[S_i \mid t] - \frac{\mu P_b(t)}{\varepsilon + \mu P_b(t)}\left[E[S_i \mid t] - \underline{S}_i\right]$$

$$A(t) = E[S_i \mid t] + \frac{\mu P_g(t)}{\varepsilon + \mu P_g(t)}\left[\overline{S}_i - E[S_i \mid t]\right]$$

$$\Sigma(t) = \frac{\mu P_g(t)}{\varepsilon + \mu P_g(t)}\left[\overline{S}_i - E[S_i \mid t]\right] + \frac{\mu P_b(t)}{\varepsilon + \mu P_b(t)}\left[E[S_i \mid t] - \underline{S}_i\right]$$

$$if\ \delta = \frac{1}{2} \Rightarrow \Sigma = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}\left[\overline{S_i} - \underline{S_i}\right]$$

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}$$

Estimating PIN in High Frequency

- Suppose that we divide the market activity in *n* volume buckets of equal size *V*. We can index these buckets as $\tau = 1, \ldots, n$.
- Let V_τ^B be the proportion of volume in a volume bucket τ associated with buying pressure, and V_τ^S associated with selling pressure.
- We know from Easley, Engle, O'Hara and Wu (2008) that the expected arrival rate of informed trades is $\mathrm{E}[V_\tau^S - V_\tau^B] = \alpha\mu(2\delta - 1)$, and $\mathrm{E}[|V_\tau^S - V_\tau^B|] \approx \alpha\mu$. The expected arrival rate of total trade is

$$\frac{1}{n}\sum_{\tau=1}^{n}\left(V_\tau^B + V_\tau^S\right) = V = \underbrace{\alpha(1-\delta)(\varepsilon+\mu+\varepsilon)}_{\text{volume from up event}} + \underbrace{\alpha\delta(\mu+\varepsilon+\varepsilon)}_{\text{volume from down event}} + \underbrace{(1-\alpha)(\varepsilon+\varepsilon)}_{\text{volume from no event}} = \alpha\mu + 2\varepsilon$$

- From the values computed above, we can derive the *Volume-Synchronized Probability of Informed Trading* (VPIN) as

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{\alpha\mu}{V} \approx VPIN = \frac{\sum_{\tau=1}^{n}|V_\tau^S - V_\tau^B|}{nV}$$

Bulk Volume Classification

- For each volume bucket τ, we can form *J* volume bars of size $\frac{V}{J}$.
- For each bar *j*, *T*% of the volume is classified as buy ***and*** (1-*T*)% as sell (denoted "**bulk classification**"). **Caution: Not all the volume of a single trade or bar is classified as buy *or* sell** (some researchers are confused by this). Then:

$$\hat{V}_\tau^B = \frac{V}{J}\sum_{j=1}^{J} T\left(\frac{P_{\tau,j} - P_{\tau,j-1}}{\sigma_{\Delta P}}, df\right)$$

$$\hat{V}_\tau^S = V\left[1 - \frac{1}{J}\sum_{j=1}^{J} T\left(\frac{P_{\tau,j} - P_{\tau,j-1}}{\sigma_{\Delta P}}, df\right)\right] = V - V_\tau^B$$

where $P_{\tau,j}$ is the last price in bar *j* within bucket τ, *T* is the CDF of the t-distribution with *df* degrees of freedom, and $\sigma_{\Delta P}$ is the estimate of the standard derivation of price changes between bars.

Bulk Volume Classification vs. Tick Rule (1/4)

- The Tick Rule (TR) and the Bulk Volume Classification (BVC) algorithms have different goals:
  - TR attempts to classify trades as buy-initiated or sell-initiated.
  - BVC determines the proportion of volume associated with buying or selling pressure.
- TR was designed for a time when most informed traders were aggressors.
- With the advent of high frequency, informed traders are increasingly relying on limit orders.
- A critical advantage of BVC is that it incorporates:
  - Buying (selling) pressure from orders resting in the bid (ask).
  - Buying (selling) pressure from cancellations in the ask (bid).

Bulk Volume Classification vs. Tick Rule (2/4)

- Market makers adjust to order imbalances, so BVC and TR should have explanatory power over high-low ranges.
- Let's define:
  - ➢ $\widehat{OI_\tau} \equiv \frac{\widehat{V_\tau^B}-\widehat{V_\tau^S}}{V_\tau} = 2\frac{\widehat{V_\tau^B}}{V_\tau} - 1$ is the estimated order imbalance.
  - ➢ $H_\tau - L_\tau$ is the difference between high and low in volume bucket τ.
- Then, we can fit the following regression model to $\widehat{OI_\tau}$ derived from BVC and TR, and apply the Newey-West HAC correction:

$$H_\tau - L_\tau = \beta_0 + \beta_1[H_{\tau-1} - L_{\tau-1}] + \gamma\left|\widehat{OI_\tau}\right| + \xi_\tau$$

Bulk Volume Classification vs. Tick Rule (3/4)

Regression Stats for BVC on WTI

Vol. Bar	aR2	NW lags	Coeff(α0)	Coeff(α1)	Coeff(γ)	t-Stat(α0)	t-Stat(α1)	t-Stat(γ)
1000	0.4170	17	5.8920	0.3143	37.8563	36.9490	43.8899	99.0193
2000	0.4656	14	7.5671	0.3310	53.1076	26.6550	35.0893	74.2852
3000	0.5045	13	7.9809	0.3560	65.7965	19.3087	33.5315	67.0455
4000	0.5124	12	8.8928	0.3554	76.2373	18.0799	31.1926	58.1366
5000	0.5186	12	9.4361	0.3648	84.7154	13.8771	25.2215	53.9255
6000	0.5317	11	9.7246	0.3716	93.9735	13.1009	25.3969	49.2206
7000	0.5332	11	9.9700	0.3771	101.8469	11.4000	24.0834	46.4617
8000	0.5319	10	10.5324	0.3711	110.4512	11.2616	23.1319	40.9419
9000	0.5311	10	11.1319	0.3641	119.0141	10.5247	21.5767	40.1135
10000	0.5351	10	11.5727	0.3657	124.8904	10.0351	21.5811	37.8392

Regression Stats for TR on WTI

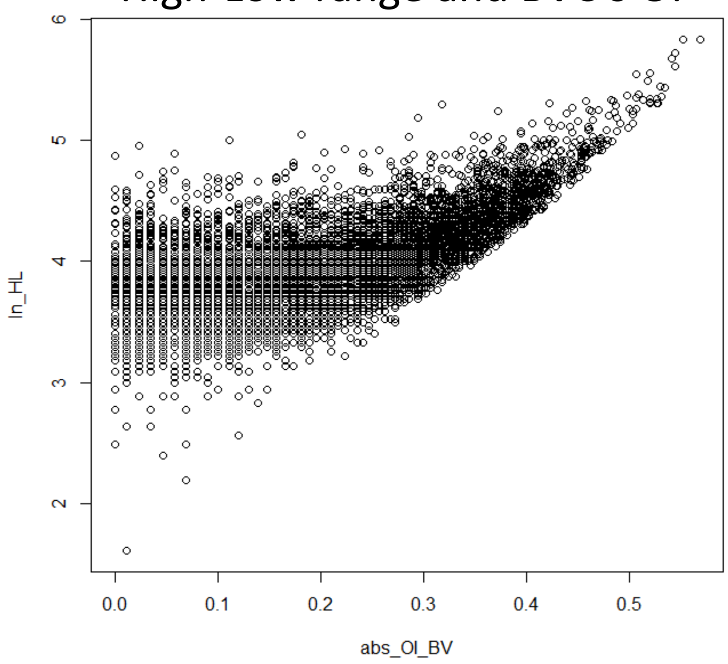
Vol. Bar	aR2	NW lags	Coeff(α0)	Coeff(α1)	Coeff(γ)	t-Stat(α0)	t-Stat(α1)	t-Stat(γ)
1000	0.1971	17	12.7006	0.4174	-5.2172	70.4226	46.7589	-25.5985
2000	0.2110	14	15.3334	0.4558	-2.1625	48.6918	39.7110	-4.5423
3000	0.2414	13	16.5738	0.4927	2.2671	37.1431	36.6620	2.6547
4000	0.2451	12	18.3786	0.4968	6.0838	34.2202	35.5162	4.8603
5000	0.2514	12	19.7551	0.5032	10.6620	25.9718	27.8923	6.3465
6000	0.2634	11	20.5196	0.5134	17.4270	24.2252	28.7296	7.4789
7000	0.2618	11	22.2337	0.5119	19.3449	22.7484	26.9841	6.9339
8000	0.2558	10	23.7416	0.5047	24.6784	21.0508	24.6193	6.8123
9000	0.2524	10	25.2300	0.5026	28.3805	20.9909	24.1256	6.9782
10000	0.2445	10	26.9771	0.4928	30.7460	19.5195	21.7657	6.3642

- BVC's estimation of Order Imbalance has significant explanatory power over high-low ranges (Note: It would be even better with a power specification).
- TR's Order Imbalance has inconsistent explanatory power (note the inconsistent signs associated with TR)
- ***Question: Why does Aggressor-Side Imbalance fail to explain the trading range?***

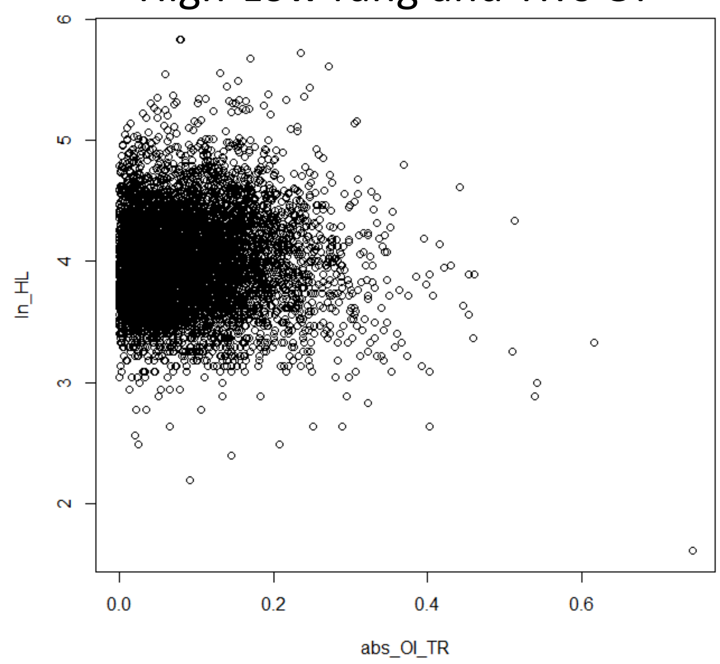
Bulk Volume Classification vs. Tick Rule (4/4)

- ***Answer***: When an informed trader slices and sequentially executes her buy order passively, sell-initiated trades coexist with her persistent buy order flow. ***Informed traders are not necessarily aggressive traders***, thus Aggressor Side-Imbalance is a deficient estimator of Order Imbalance.

High-Low range and BVC's OI



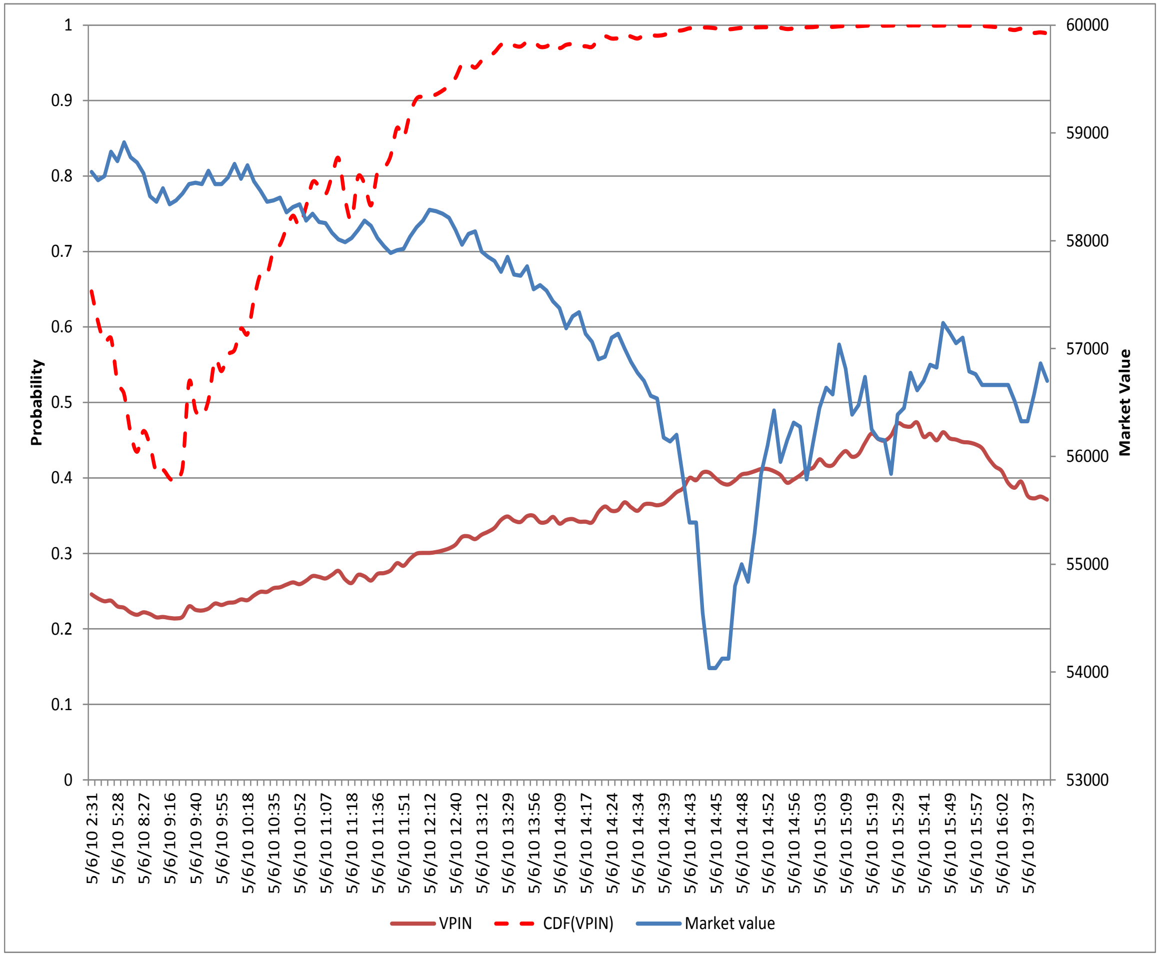
High-Low rang and TR's OI



Does the PIN Theory work in practice?

- Multiple empirical microstructure studies have found that order flow imbalance impacts trading ranges (e.g., Eisler et al. [2012])
- VPIN formalizes that empirical finding by providing the theoretical connection between *order flow imbalance* ($|V_\tau^S - V_\tau^B|$) and the *range at which market makers provide liquidity* (Σ).
- Through VPIN, we can apply the PIN theory to study:
  - Bid-ask dynamics and liquidity crises.
  - Toxicity-induced volatility.
  - Transaction cost functions and execution strategies.

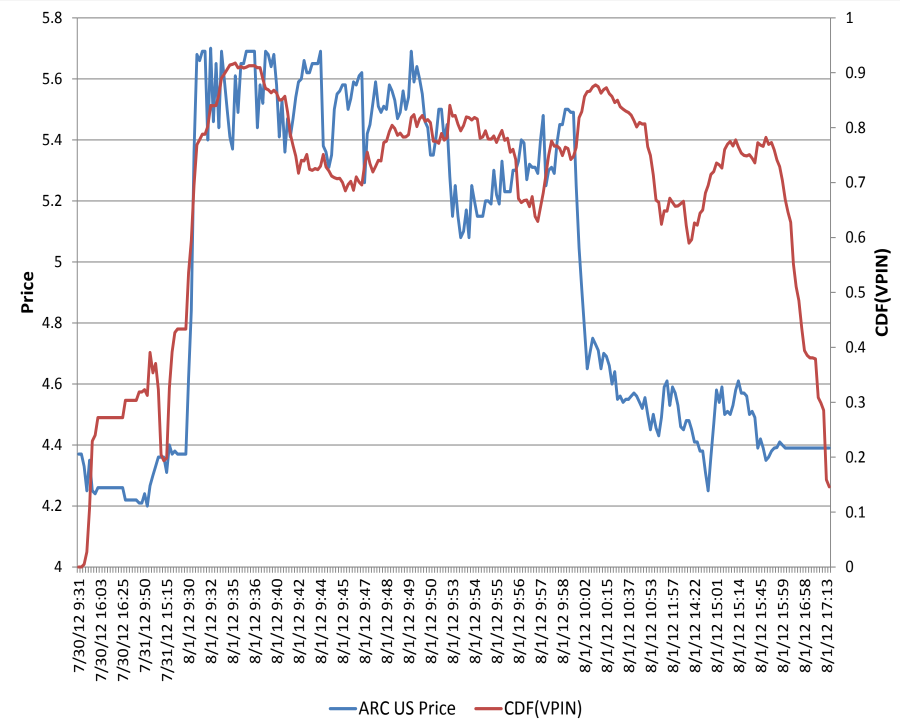
E-mini S&P500 futures on 05/06/10

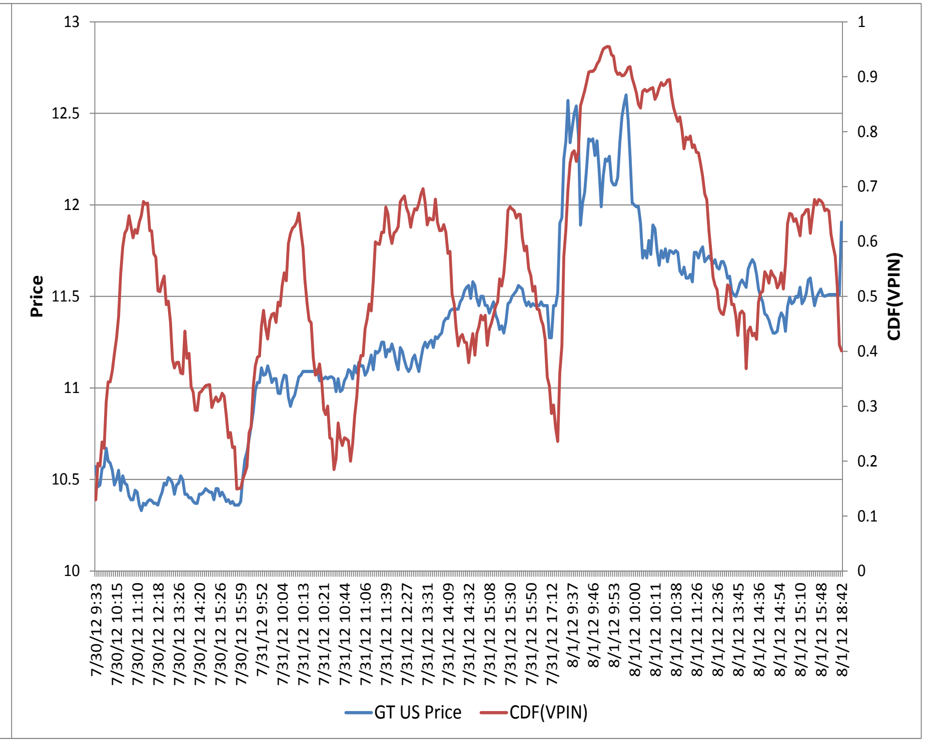


By 11:56am, the realized value of the VPIN metric was in the 10% tail of the distribution (it exceeded a 90% CDF(VPIN) critical value). By 1:08pm, the realized value of VPIN was in the 5% tail of the distribution (over a 95% CDF(VPIN)). At 2:32pm the crash begins according to the CFTC-SEC Report time line. Link to video.

Note: The May 6th 2010 'Flash Crash' is just one of hundreds of liquidity events explained by VPIN!

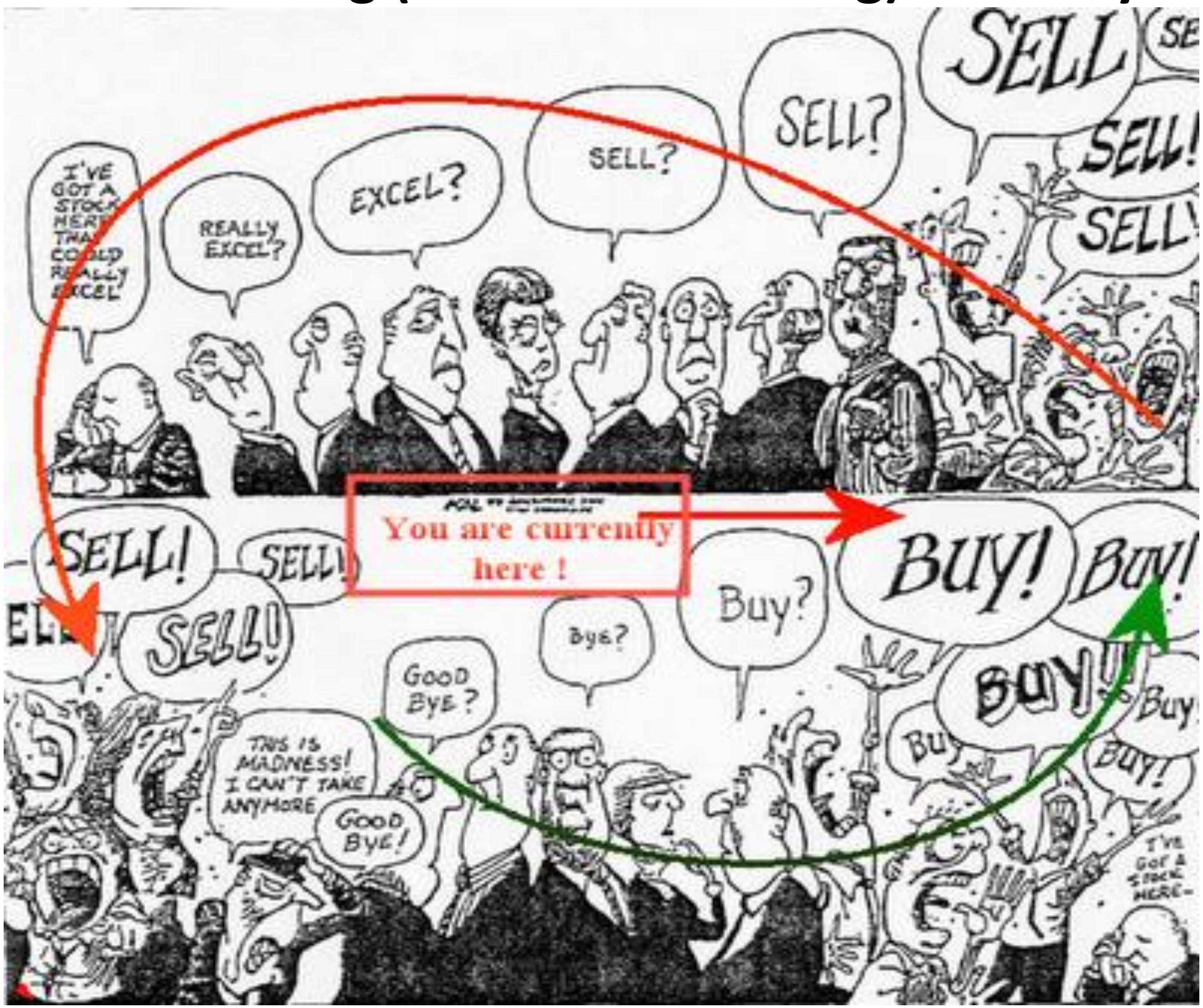
The “Knight-mare” of 08/01/12





Trades for ARC US (American Reprographics) were cancelled, not for GT US (Goodyear). In both cases, CDF(VPIN) jumps to high levels within a few minutes of the open. Prices also jumped, but the relevant piece is that the price jump occurred as a result of **persistent order imbalance**. It was the result of overwhelming and uninterrupted buying pressure (which lasted for 44 minutes), rather than a price adjustment to new information. Knight’s platforms should have picked this up and pulled orders automatically.

SECTION III
Forecasting (and understanding) Volatility



Forecasting Toxicity-induced volatility (1/4)

- An event *e* occurs every time that $CDF[VPIN(\tau)] \geq CDF^*$ while $CDF[VPIN(\tau-1)] < CDF^*$. We can index those events as $e = 1, \ldots, E$, and record the volume bucket at which $CDF[VPIN(\tau)]$ crossed the threshold CDF^* as $\tau(e)$

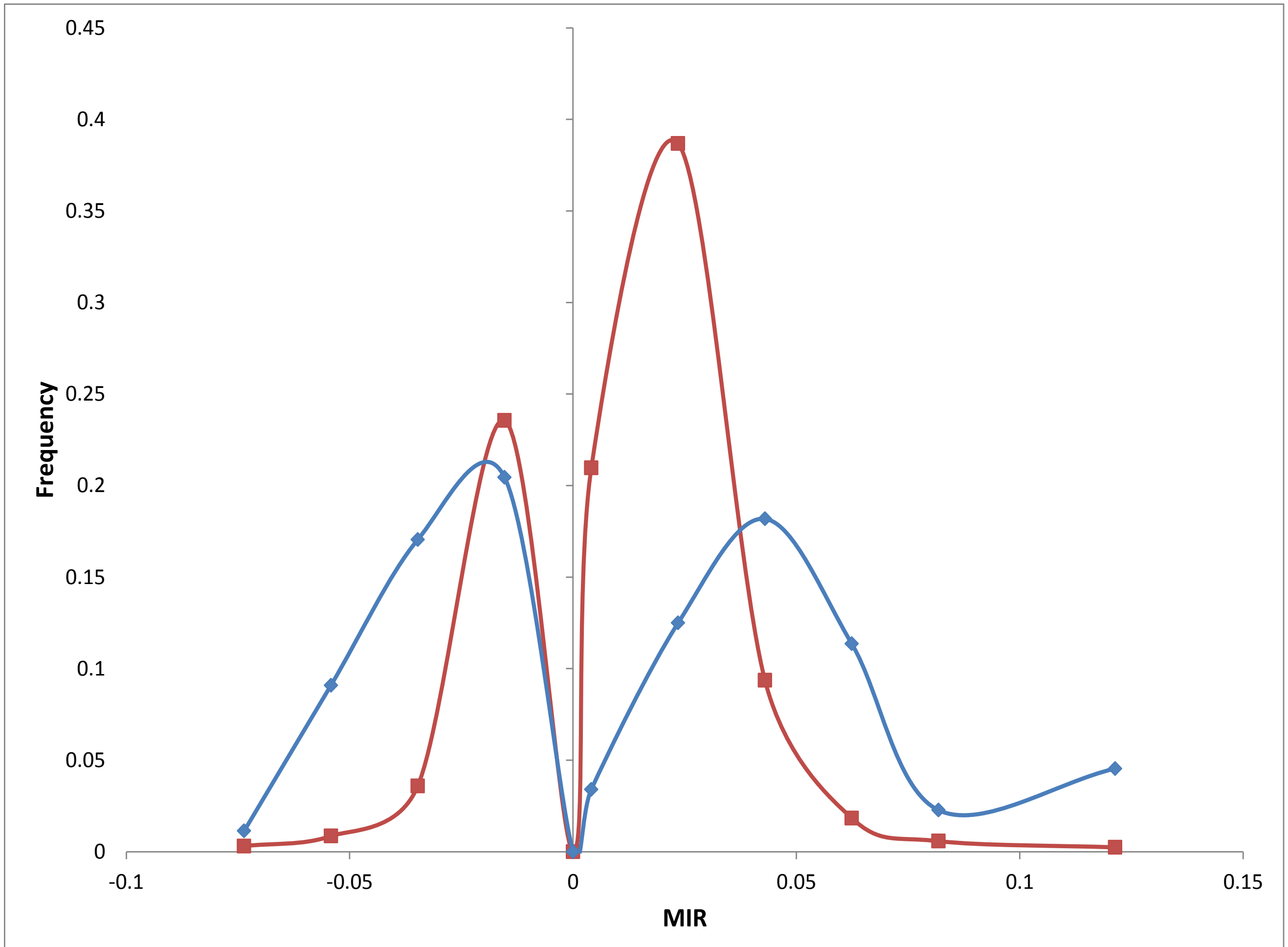
- For each particular *e*, Event Horizon h(*e*) is defined as

$$h(e) = \{h_0(e), h_1(e)\} = arg \max_{\substack{0 \leq h_0 < h_1 \\ 1 \leq h_1 \leq BpD}} \left| \frac{P_{\tau(e)+h_1}}{P_{\tau(e)+h_0}} - 1 \right|$$

- Similarly, Maximum Intermediate Return MIR(e) is defined

$$MIR(e) = \frac{P_{\tau(e)+h_1(e)}}{P_{\tau(e)+h_0(e)}} - 1$$

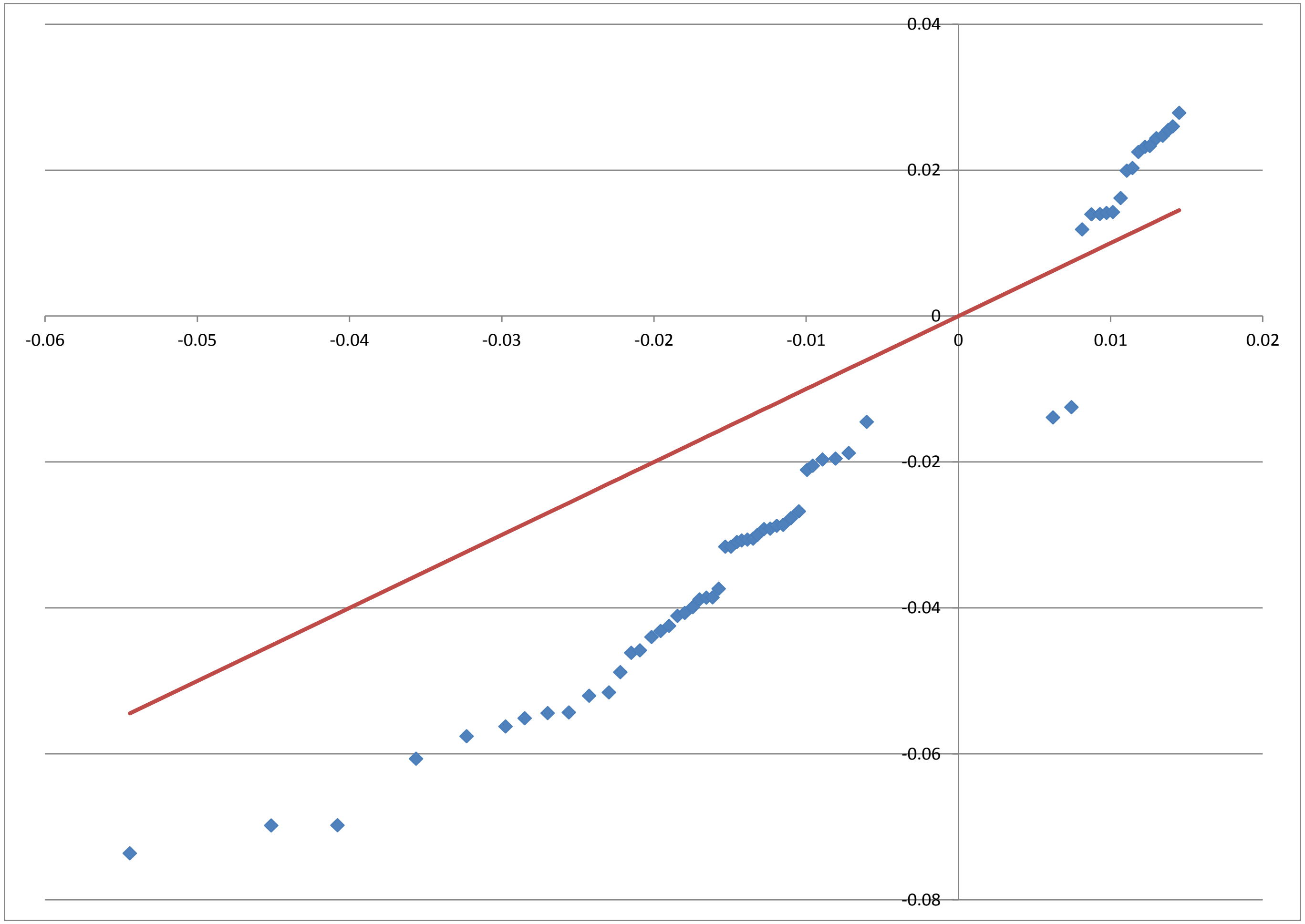
Forecasting Toxicity-induced volatility (2/4)



We have computed two distributions of probability: One for MIRs following an event *e* (in blue), and another one for MIRs at random starts (in red).

Following an event *e*, most MIR (blue) fall within one of the two tails of the unconstrained distribution (red). High volatility occurred *after* VPIN crossed the designated threshold

Forecasting Toxicity-induced volatility (3/4)



This qq-plot shows that both distributions are clearly different: VPIN events are not random and indeed have consequences in terms of non-standard MIR).

This is consistent with most (blue) $MIR(e)$ falling at the tails of unconstrained *MIR* (red).

Forecasting Toxicity-induced volatility (4/4)

BDP	D	Events	eMean	eStd	uMean	uStd	KS_Stat	KS_CDF
25	0.2	239	0.02819	0.01628	0.01860	0.011903	0.19171	1.00000
25	0.5	144	0.03149	0.01597	0.01860	0.011903	0.24984	1.00000
25	1	81	0.03554	0.01727	0.01860	0.011903	0.31130	1.00000
50	0.2	257	0.03051	0.01716	0.01951	0.012073	0.24169	1.00000
50	0.5	124	0.03392	0.01681	0.01951	0.012073	0.26478	1.00000
50	1	73	0.03499	0.01570	0.01951	0.012073	0.32145	1.00000
75	0.2	241	0.03166	0.01707	0.01969	0.012319	0.25774	1.00000
75	0.5	121	0.03552	0.01759	0.01969	0.012319	0.26242	1.00000
75	1	64	0.03761	0.01713	0.01969	0.012319	0.32163	1.00000
100	0.2	244	0.03127	0.01667	0.02010	0.012236	0.19684	1.00000
100	0.5	142	0.03470	0.01809	0.02010	0.012236	0.26960	1.00000
100	1	88	0.03912	0.01913	0.02010	0.012236	0.32815	1.00000

The intermediate returns that follow high VPIN events have a mean (eMean) that is up to 100% greater than the intermediate returns at random events (uMean). The table above compares those means and standard deviations (eStd, uStd), for the Events identified through various combinations of Buckets per Day (BPD) and Days of Sample (D).

SECTION IV
What can Low Frequency Traders do?

If you cannot defeat them… (1/5)

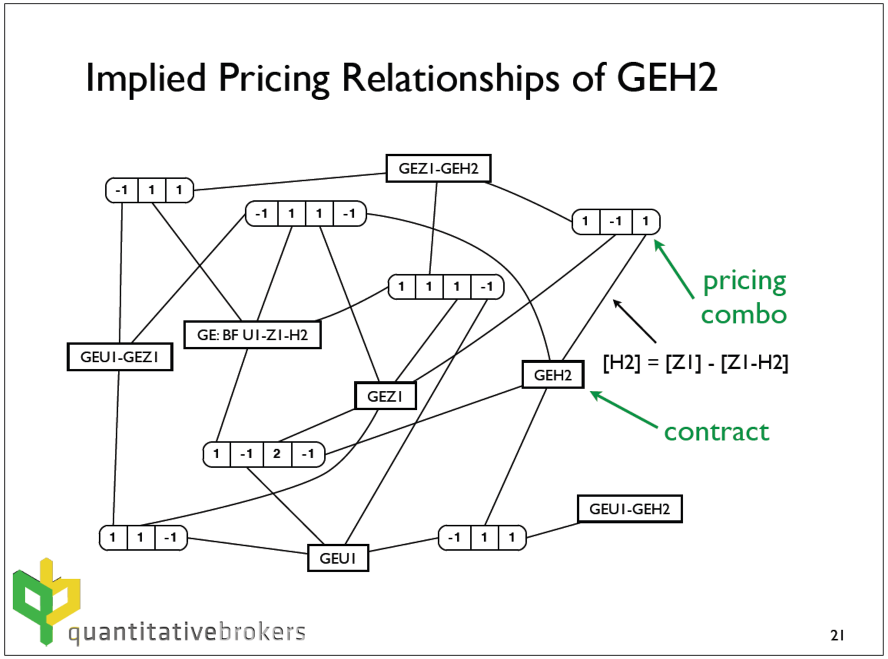
- Volume-time is a particular case of *"subordinated stochastic process"*, which can be traced back to Mandelbrot and Clark's work in the early 70s.
- Any concentration of information per unit of trading is susceptible of being recognized and taken advantage from. We have seen this with TWAP algos and round-number orders, but there are many more examples.
- Part of HFT's success is due to the reluctance of LFT to adopt their paradigm. **LFT Choice #1: Where possible, adopt the HFT paradigm.**

If you cannot defeat them… (2/5)

- There is some evidence that "big data" is not necessarily an advantage in all instances.
- For example, Easley et al. [2012b] show that "bulk volume classification" determines the aggressor side of a trade with greater accuracy than the tick rule applied on tick data!
- The same authors show that low-frequency statistics (like VPIN) can detect the presence of informed traders and determine the optimal trading horizon.
- **LFT Choice #2: Develop statistics to monitor HFT activity and take advantage of their weaknesses.**

If you cannot defeat them… (3/5)

- Over 50% of the trades on Index Futures in 2011 were for 1 contract. Trades of 100 contracts are 17 times more frequent than trades of size 99 or 101.

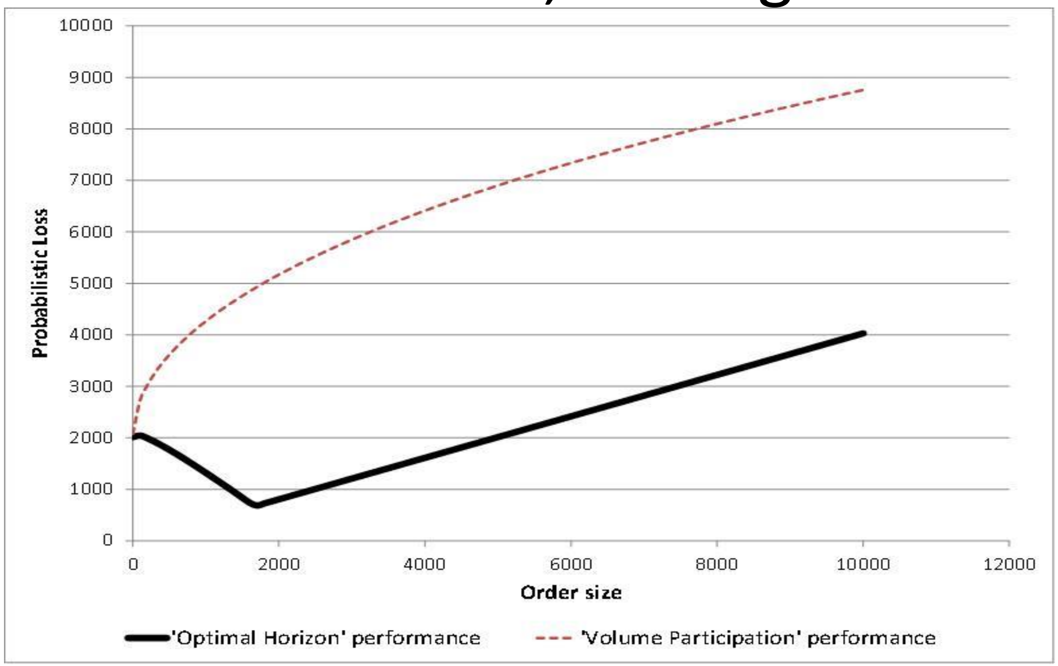


HFT algos can easily detect when there is a human in the trading room, and take advantage. We have seen that the cost of not concealing trading intentions could be up to 40% of a trade's profit target (forecasted alpha).

- **LFT Choice #3: Use "smart algos", specialized in searching for liquidity and avoiding a footprint.**

If you cannot defeat them… (4/5)

- Participation rate strategies do not take into account the market's state, leaving an identifiable footprint.



Comparison of the probabilistic loss values for the OEH algorithm versus a scheme that participates in 5% of the volume. $v^B = 0.4$.

- **LFT Choice #4: Do not target a participation rate. Instead, determine the optimal execution that fits the prevalent market conditions.**

If you cannot defeat them… (5/5)

- Toxic order flow disrupts the liquidity provision process by adversely selecting market makers.
- An exchange that prevents such disruptions will attract further liquidity, which in turn increases the corporate value of its products.
- A way to avoid disruptions is to make harder for predators to operate in that exchange.
- **LFT Choice #5: Trade in exchanges that incorporate smart circuit breakers and matching engines.**

Conclusions

- Orders from informed traders generate a persistent order flow imbalance.
- Market makers adjust their trading range accordingly, in order to avoid adverse selection.
- Market makers operate in a Volume Clock, an are particularly susceptible to imbalances in that frequency.
- **The key to optimal execution is to minimize the footprint of your trades on the order flow in volume clock.**
- The Optimal Execution Horizon (OEH) algorithm determines the amount of volume needed to conceal the intentions of an informed trader.

THANKS FOR YOUR ATTENTION!

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Bio

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Marcos is a scientific advisor to *Enthought*'s Python projects (NumPy, SciPy), and a member of the editorial board of the Journal of Investment Strategies (Risk Journals). His research has resulted in three international patent applications, several papers listed among the most read in Finance (SSRN), publications in the Review of Financial Studies, Journal of Risk, Journal of Portfolio Management, etc. His current Erdös number is 3, with a valence of 2.

Notice:

The research contained in this presentation is the result of a continuing collaboration with

Prof. Maureen O’Hara
Prof. David Easley

The full paper is available at:
http://ssrn.com/abstract=1695596

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