# THE VOLUME CLOCK:
# INSIGHTS INTO THE HIGH FREQUENCY PARADIGM

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## ABSTRACT

Over the last two centuries, technological advantages have allowed some traders to be faster than others. We argue that, contrary to popular perception, speed is not the defining characteristic that sets High Frequency Trading (HFT) apart. HFT is the natural evolution of a new trading paradigm that is characterized by strategic decisions made in a volume-clock metric. Even if the speed advantage disappears, HFT will evolve to continue exploiting Low Frequency Trading's (LFT) structural weaknesses. However, LFT practitioners are not defenseless against HFT players, and we offer options that can help them survive and adapt to this new environment.



**Keywords**: High-frequency trading, low-frequency trading, predatory algorithm, volume clock, chronological clock.

**JEL codes**: D52, D53, G02.

## THE GREAT DIVIDE

Legend holds that Nathan Mayer Rothschild used racing pigeons to front run his competitors and trade on the news of Napoleon's defeat at Waterloo a full day ahead of His Majesty's official messengers (Gray and Aspey [2004]). Whether this story is true or not, it is unquestionable that there have always been faster traders. Leinweber [2009] relates many instances in which technological breakthroughs have been used to most investors' disadvantage. The telegraph gave an enormous edge to some investors over others in the 1850s, perhaps to a greater extent than the advantages enjoyed today by high frequency traders. The same could be said of telephone traders in the 1875s, radio traders in the 1915s, screen traders in 1986, to cite only a few known examples. Since there have always been faster traders … what is new this time around? If there is something truly novel about high frequency trading (HFT), it cannot be only speed.

And yet, high-frequency traders have been characterized as 'cheetah traders', an uncomplimentary allusion to their speed and character. The reality is, as usual, more complex. Today's high frequency markets are not the old low frequency markets on steroids. To be sure, speed is an important component of high frequency's success. However, in this article we will argue that there is much more to it. We will make the case that what lies at the center of HFT is a change in paradigm.

## THE NEW TRADING PARADIGM

The 'flash crash' of May 6, 2010 pushed HFT into the spotlight. To understand what led to the emergence of high frequency trading, however, we have to turn the clock back five years earlier. HFT strategies were made possible by legislative changes in the United States

(“Regulation National Market System” of 2005, or “Reg NMS”) and Europe (“Markets in Financial Instruments Directive” or “MiFID”, in force since November 2007), preceded by substantial technological advances in computation and communication. High-speed trading had been technologically possible for many years, but it was legislative action that made HFT profitable.

Europe’s MiFID fostered greater competition among brokers, with the objective of improving liquidity, cohesion and depth in financial markets. MiFID allowed for new, highly technological competitors to enter the European markets, thereby introducing competition for what had been a relatively quiescent, exchange-dominated market structure. Similarly, U.S. Reg NMS encouraged competitiveness among exchanges by allowing market fragmentation. At this, Reg NMS was wildly successful, as the current market structure of 13 equity exchanges and 40 or more alternative venues (dark pools, dealer desks, etc.) attests. Cohesion was supposedly ensured in the U.S. through a mechanism for the consolidation of individual orders processed via multiple venues (the NBBO, or “National Best Bid and Offer”).[1] These changes, combined with decimalization of equity markets, resulted in an “arms race” for developing the technology and quantitative methods that could extract the last cent of profitability from trading while serving the demands of market participants.

The high frequency strategies that developed are actually very diverse. It would be a mistake, for example, to conflate the HFT strategies of cash equities and the HFT strategies of futures on equity indices. The reason is that HFT is not particularly related to macro factors (such as asset class), but it is intimately related to market microstructural factors. While cash

[1] O’Hara and Ye [2011] present evidence that fragmentation has not degraded market quality in the U.S. Thus, Reg NMS accomplished its goal of creating a single virtual market with many points of entry.

equity markets are fragmented and decimalized, the markets for equity futures are not, and so the first type of HFT strategies have little in common with the second.

Many high frequency strategies model the dynamics of the double auction book. This allows HFTs to place numerous independent bets every day on the same instrument or portfolio, thus taking advantage of the multiplicative effect postulated by the “Fundamental Law of Active Management”, i.e., that a tiny predictive power on a sufficiently large number of independent bets yields a high Information Ratio and thus a profit (see Grinold [1989]). The goal is to exploit the inefficiencies derived from the market’s microstructure, such as rigidities in price adjustment within and across markets, agents’ idiosyncratic behavior, and asymmetric information. As a consequence of this higher frequency, the identification of opportunities, risk control, execution and other investment management activities must be automated. Not all algorithmic trading occurs in high frequency, but all high frequency requires algorithmic trading.

It is useful to contrast the divergent worlds of the low frequency traders (LFTs) and the HFTs. Financial Analysts’ Conferences are one milieu where low frequency traders (LFT) converse on subjects as broad and complex as monetary policy, asset allocation, stock valuations, financial statement analysis, and the like. HFT Conferences are reunions where computer scientists meet to discuss TCP/IP connections, machine learning, numeric algorithms to determine the position of an order in a queue, the newest low-latency co-location architecture, game theory, and most important of all, the latest variations to exchanges’ matching engines. One would conclude, correctly, that the LFTs and the HFTs are seemingly worlds apart.

The issues surrounding exchange matching engines are a case in point. Economists and finance professionals often talk about the market’s auctioning process as a given, but it is microstructure theorists who wade into the minutia of how prices and volumes are actually formed. Because the devil is in the details, how exactly the order flow is handled, and thus how trades and prices are formed, provides potential profits for those who understand these market dynamics (see Exhibit 1). Over short intervals of time, prices are not the random walks so beloved by the Efficient Market Hypothesis, but can instead be predictable artifacts of the market microstructure. Thus, the paradox of all the billions invested in HFT research and infrastructure on a topic that LFTs do not even recognize as an issue.

[EXHIBIT 1 HERE]

Given their dissimilar backgrounds, it is hardly surprising that HFT professionals would operate under a different paradigm than their LFT peers. But how did this different background translate into a new investment paradigm?

## THE MEANING OF TIME

Time can be understood as 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, more recently, milliseconds, microseconds... Because we have been brought up to think in terms of chronological time, we can hardly visualize a different way of scheduling our lives. However, this is a rather arbitrary time system, arguably due to the key role played by the sun in agrarian societies.

Machines operate on an internal clock that is not chronological, but event-based: The *cycle*. A machine will complete a cycle at various chrono rates, depending on the amount of information and complexity involved in a particular instruction. For the reasons mentioned earlier, HFT relies on machines, thus measuring time in terms of events is only natural. Thinking in volume-time (or any other index of activity) is challenging for us humans. But for a ‘silicon trader', it is the natural way to process information and engage in sequential, strategic trading. 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 an attempt to keep a certain market share.

The paradigm in this world is "*event-based time*". The simplest example is dividing the session into equal volume buckets (e.g. in 200,000 contract increments, or 20,000 share buckets). In fact, working in volume time presents significant statistical advantages. First, this time transformation removes most intra-session seasonal effects; second, it allows a partial recovery of Normality and the IID assumption; third, sampling in a volume-clock metric addresses the problem of random and asynchronous transactions, which is a major concern when computing correlations on high-frequency data.[2]

The idea of modeling financial series using a different time clock can be traced back to the seminal work of Mandelbrot and Taylor [1967] and Clark [1970; 1973]. Ané and Geman [2000] is another notable, more recent contribution. Mandelbrot and Taylor open their paper with the assertion:

> *"Price changes over a fixed number of transactions may have a Gaussian distribution. Price changes over a fixed time period may follow a stable Paretian distribution, whose variance is infinite. Since the number of transactions in any time period is random, the above statements are not necessarily in disagreement. […] Basically, our point is this: the Gaussian random walk as applied to transactions is compatible with a symmetric stable Paretian random walk as applied to fixed time intervals."*

In other words, these two authors advocated for recovering Normality through a transaction-based clock, moving away from chronological time. This would treat equally

[2] A HFT application can be found in Easley et al. [2012a]

transactions of different size. Clark [1973] suggested a related variant, arguing for a volume-based clock. Mandelbrot [1973] explained the difference between them in the following terms:

> *"There is -as I have said- no dispute between us about the value of the concept of subordinated process. Clark's approach is an interesting and natural modification of one described by Mandelbrot and Taylor. The notion is that price change would cease to be erratic and would reduce to the familiar Brownian motion if only it were followed in an appropriate "local time" different from "clock time". Taylor and I had thought that local time might coincide with transaction time, while Clark links it with volume. He also has the merit of having investigated this hunch empirically……. However, it should be kept in mind that if price variation is to proceed smoothly in local time, then local time itself must flow at random and at a highly variable rate. Consequently, as long as the flow of local time remains unpredictable, concrete identification of the applicable local time leaves the problems of economic prediction unaffected."*

Mandelbrot's rather negative conclusion regarding the role of "local time" reflected a basic reality of the markets in his day: The decisions that participants made were all based on chronological time, such as estimating volatilities over a day or returns over a month. Consequently, recovering Normality in what he called "local time" (i.e., transaction or volume-time) did not seem helpful, because there is no way to translate the forecast back into chronological time. However, as we have argued, HFT operates in event-based time (such as transaction or volume), thus removing the need for this translation. HFT will monetize accurate forecasts of E-mini S&P500 Futures volatility over the next 50,000 contracts, whatever the number of (night-session) hours or (day-session) milliseconds it takes to exchange that volume. A HFT market maker has little use for a model that attempts to forecast volatility over a chronological time horizon, because she must keep her inventory under control in volume time (e.g., by turning her inventory over for every 50,000 contracts exchanged). Being closer to actual Normality and independence of observations (see Exhibit 2) allows for applying standard statistical techniques, which means faster calculations, shorter cycles and thus faster reaction.

[EXHIBIT 2 HERE]

The upshot of this new paradigm is clear:  Even if connectivity speed ceased to be a significant edge, HFT would and will exist.

**MORE THAN SPEED**

Easley et al. [1996] linked liquidity to informational asymmetry by identifying how market makers adjust their bid-ask spreads to the probability of informed trading (PIN). Because informed traders monetize their superior knowledge of a security's future price by adversely selecting uninformed traders, market makers must update their quoted levels and sizes in real time in a manner that reflects their estimate of PIN. HFT reacts to information leaked by LFT in order to anticipate their actions. DMA (Direct Market Access) allows the deployment of this kind of strategic sequential trading logic to market venues.

To be clear, strategic sequential trading is not particular to HFT. In October 1990, the British Pound joined the European Exchange Rate Mechanism (ERM). Under that agreement, the Government would have to intervene in order to ensure that the exchange rate between the pound and other currencies would not fluctuate beyond a 6% band. Traders knew that, with an inflation rate 3 times that of Germany despite high interest rates, in addition to double digit deficits, the British Government's position was extremely vulnerable. Thus, a strategy could be devised to take advantage of that Government's predictable behavior. On September 16, 1992 (Black Wednesday) a group of speculators launched an uncoordinated attack to force the withdrawal of the British Pound from the ERM.[3]

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[3] HM Treasury, *"Reflections on the UK's membership of the ERM"*, January 5, 1994. Available at http://webarchive.nationalarchives.gov.uk/+/http://www.hm-treasury.gov.uk/about/information/foi_disclosures/foi_erm4_090205.cfm

What makes HFT such a great example of strategic sequential trading is its "event-based" interaction with the exchange's matching engine through DMA. Its decision making process is synchronized with the speed at which actions take place, thus acting upon the revelation of new information. A good metaphor of strategic sequential trading can be found in poker or chess. A chess player makes moves at different speeds during a game, depending on several factors: Superiority over the adversary, stage of the game, amount of material lost, computational power, experience with the existing position, time remaining before the end of the game, etc. It would make little sense for a chess player to attempt making moves every minute (even if that were possible), but rather moves take place whenever the processing of the new information permits, according to the aforementioned factors. With every move, each player reveals information about her knowledge of the game, which can be used by an experienced adversary to lead the opponent to an uncomfortable situation. Once the adversary has made a move, the player has new information on the board to be *cycled*. Players try to anticipate each other's moves several steps ahead, and force the adversary to make an error. The next move is *conditional* upon the opponent's previous moves as well as her own. There are sacrifices, calculated "mistakes" and a lot of deception. All of these features are present in HFT.

Predatory algorithms constitute a very distinct species of informed traders, because of the nature of their information and the frequency of their actions. Such HFT algorithms exploit a microstructural opportunity in a similar way that large speculators exploit a macroeconomic inconsistency. 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. Their advent has transformed liquidity provision into a tactical game. A few examples discussed in the literature include:

- *Quote stuffers*: They engage in 'latency arbitrage'. The strategy involves overwhelming an exchange with messages, with the sole intention of slowing down competing algorithms, which are forced to parse messages that only the originators know that can be ignored.[4]
- *Quote danglers*: This strategy sends quotes that force a squeezed trader to chase a price against her interests. O'Hara [2011] presents evidence of their disruptive activities.
- *Liquidity squeezers*: When a distressed large investor is forced to unwind her position, they trade in the same direction, draining as much liquidity as possible. As a result, prices overshoot and they make a profit (Carlin, Sousa Lobo and Viswanathan [2007]).
- *Pack hunters*: Predators hunting independently become aware of each other's activities, and form a pack in order to maximize the chances of triggering a cascading effect (Donefer [2010], Fabozzi, Focardi and Jonas [2011], Jarrow and Protter [2011]). NANEX [2011] shows what appears to be pack hunters forcing a stop loss. Although their individual actions are too small to raise the regulator's suspicion, their collective action may be market-manipulative. When that is the case, it is very hard to prove their collusion, since they coordinate in a decentralized, spontaneous manner.

Arnuk and Saluzzi [2009] were among the first to highlight the dangerous trend in order cancellation rates. The SEC[2011] admits that "a vast majority" of orders are now cancelled (estimates by TABB group put this at 98%)[5], and is exploring "ways to fairly allocate the costs imposed by high levels of order cancellations, including perhaps requiring a uniform fee across all Exchange markets that is assessed based on the average of order cancellations to actual transactions effected by a market participant" (p.13).

Because of the threat posed by predators, high frequency liquidity providers must be much more tactical (see Exhibit 3 for an example). Sometimes they may suddenly pull all orders, liquidate their positions and stop providing liquidity altogether. This decision has more to do with computer science and game theory than it does with valuation fundamentals. The resulting price actions may seem absurd from an economic perspective, but because the actors made their

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[4] NANEX, *"Analysis of the 'Flash Crash'"*, June 18, 2010. Available at http://www.nanex.net/20100506/FlashCrashAnalysis_CompleteText.html

[5] See "*SEC May Ticket Speeding Traders*," Wall Street Journal, February 23, 2012.

decisions applying a different rationale their behavior is perfectly sensible.[6] Carlin, Sousa Lobo, and Viswanathan [2007] model how predatory trading can lead to episodic liquidity crises and contagion.

[EXHIBIT 3 HERE]

For the HFT trader, the name of the game is not to move as fast as possible, but rather to make the best possible move (before a competitor does) with the information revealed. To understand what this implies for market behavior, consider the simple issue of trade size. Easley et at. [2012b] report that more than 50% of trades in the S&P500 E-mini futures are now for 1 contract. Trade frequency quickly drops beyond sizes over 10. However, trades of size 100 are up to 17 times more frequent than trades of size 99 or 101 in the e-Mini S&P500. The reason is that many GUI (Graphical User Interface) traders have buttons for sizes with round numbers. HFT algorithms know that if many participants are operating with round numbers in a given moment of the trading session, the market is likely to behave in a particular way. Even though trading algorithms are not intelligent in the human sense (at least not yet), machine learning and game theory allows them to identify deep patterns in market activity. Predictable behavior can then be taken advantage of by silicon traders.

Databases with trillions of observations are now commonplace in financial firms. Machine learning methods, such as Nearest Neighbor or Multivariate Embedding algorithms search for patterns within a library of recorded events. This ability to process and learn from what is known as "big data" only reinforces the advantages of HFT's "event-time" paradigm, very much like how "Deep Blue" could assign probabilities to Kasparov's next 20 moves, based

[6] S.E.C. Chairman Mary Shapiro made this point in her *"Testimony Concerning the Severe Market Disruption on May 6, 2010"* before the Subcommittee on Capital Markets, Insurance and Government Sponsored Enterprises of the United States House of Representatives Committee on Financial Services. May 11, 2010. Available at http://sec.gov/news/testimony/2010/ts051110mls.pdf

on hundreds of thousands of past games (or more recently, why Watson could outplay his Jeopardy opponents).

The upshot is that speed makes HFTs more effective, but slowing them down won't change their basic behavior: Strategic sequential trading in event time.

**LIKE SHEEP AMONG WOLVES?**

A number of studies have found that HFT is beneficial in many ways (see Broogard [2012]; O'Hara and Linton [2011]; Hasbrouck and Saar [2011]). Evidence suggests that HFT has added liquidity to the markets, narrowed spreads, and enhanced informational efficiency. But other studies, like Zhang [2010], find evidence that HFT heightens volatility. There are also concerns that HFT liquidity providers are too tactical in nature (they can vanish when most needed). In addition, there are clearly substantial expenses needed for LFTs to develop countermeasures against predatory algorithms. The debate regarding the social benefit of HFT is far from closed.

What does appear clear is that HFT cannot be un-invented, or regulated away, without some severe market effects. HFT now controls the liquidity provision process, and over 70% of all U.S. cash equity trades involve a high frequency counterpart (Iati [2009]). HFT participation in futures is similarly important, with estimates ranging to more than 50%. While debates rage over regulatory control, there is little consensus as to what is desirable, or even feasible. National Tobin taxes are doomed to fail, and an international agreement is unlikely. It is not even clear that they would do any good, other than change the rules of the game, to which HFT strategies can easily adapt. An alternative that seems closer to the core of the HFT paradigm is a tax on FIX messages (as opposed to a tax on transactions). Some exchanges and regulators are proposing charges on message traffic, but this would also affect algorithmic trading by LFTs, a form of "collateral damage" that seems undesirable. More to the point, such changes would not completely eliminate all sequential strategic behavior. The new paradigm that underlies HFT is not really about speed, so regulatory efforts to slow "cheetah traders" miss the larger point that what is undesirable are particular manipulative strategies and not HFT per se.

There is no question that the goal of many HFT strategies is to profit from LFT's mistakes. Exhibit 4 shows how easy this has become. We have taken a sample of E-mini S&P500 futures trades between 11/07/2010 and 11/07/2011. We have divided the day in 24 hours (y-axis), and for every hour, added the volume traded at each second (x-axis), irrespective of the minute. For example, E-mini S&P500 futures trades that occur at 20:20:01 GMT and 20:23:01 GMT are added together.[7] This analysis allows us to see the distribution of volume within each minute as the day passes, and search for LFTs executing their massive trades on a chronological time-space. The largest concentrations of volume within a minute tend to occur during the first few seconds, for almost every hour of the day. This is particularly true at 02:00-03:00 GMT (around the open of European equities), 13:00-14:00 GMT (around the open of U.S. equities) and 20:00-21:00 GMT (around the close of U.S. equities). This is the result of TWAP algorithms and VWAP algorithms that trade on 1 minute slots. A mildly sophisticated HFT algorithm will evaluate the order imbalance at the beginning of every minute, and realize that this is a persistent component, thus front-running VWAPs and TWAPs while they still have to execute the largest part of the trade.

[EXHIBIT 4 HERE]

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[7] We are using the GMT convention for time, as GLOBEX does.

This is just one example of how vulnerable the "chronological time" paradigm has made LFTs, but there are dozens of instances like this. Easley et al. [2012b] show that about 51.56% of E-mini S&P500 futures trades between 11/07/2010 and 11/07/2011 were for one contract. For example, orders of size 10 are 2.9 times more frequent than orders of size 9. Size 50 is 10.86 times more likely than size 49. Because 'GUI traders' tend to submit round order sizes, 'silicon traders' can easily detect when there is a disproportionate presence of humans in the market and act on that knowledge. These behaviors are a likely cause of the increasing number of short-term liquidity crises over the past few years.

But just as markets have evolved, so, too, can LFTs. Part of HFT's success is due to the reluctance of LFT to adopt (or even to recognize) their paradigm. We believe that LFT players have multiple choices to survive in this new HFT era. These include:

**Choice #1: Where possible, LFT firms should adopt the HFT "event-based time" paradigm**. For issues such as portfolio selection, event-based time may not seem particularly relevant. There is an increasing awareness, however, that alpha capture cannot be done in isolation from trading – i.e. the implementation of portfolio selection requires trading, and this places it firmly in the purview of the HFT world. The best portfolio selection ability is useless if HFT algos can free-ride on your trades and drive up your execution costs.

**Choice #2: Develop statistics to monitor HFT activity and take advantage of their weaknesses**. There is some evidence that "big data" is not necessarily an advantage in all instances. For example, in other work (see Easley et al. [2012b]) we found that "bulk volume classification" determines the aggressor side of a trade with greater accuracy than the tick rule applied on tick data! We also show that lower-frequency statistics (like VPIN) can detect the toxicity in the market and determine the optimal trading horizon. Monitoring market conditions for high toxicity can be particularly beneficial for LFTs. In the 'flash crash', the Waddell and Reed trader would surely have been well advised to defer trading rather than to sell, as they did, in a market experiencing historically high toxicity levels.

**Choice #3: Join the herd.** Trade with volume bursts, like at the opening and closing of the session, when your footprint is harder to be detected. Transactions cost now largely consist of price impact cost, and astute LFTs must use TCA (transaction cost analysis) products that are predictive, rather than simply reactive. Naïve trading strategies are simply bait for predatory algos.

**Choice #4: Use "smart brokers", specialized in searching for liquidity and avoiding a footprint**. As we have seen, HFT algos can easily detect when there is a human in the trading room, and take advantage. Advanced brokers use HFT technology in a different way. Rather than attempting to identify patterns for alpha-generation purposes, they avoid actions that may leave recognizable footprints. For example, TWAP is highly predictable and should be avoided. VWAP joins the herd, however in a predictable way. VWAP algos are insensitive to the damage done to liquidity providers. A smart VWAP algo would incorporate a feedback mechanism that adjusts the execution horizon in real time, as it recognizes the damage done by prior child orders. New algorithms by the more sophisticated brokers use volume patterns, dark executions and the like to reduce the footprint of their trades (see Easley et al. (2012c) for an example).

**Choice #5: Trade in exchanges that incorporate technology to monitor order flow toxicity**. 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. One way to avoid disruptions is to make it harder for predators to operate in that exchange. Exchanges have been changing their trading systems to cater to HFTs (and the resulting liquidity they provide). But exchanges could also modify their matching engines to respond to toxicity changes that can impair liquidity provision to LFTs.

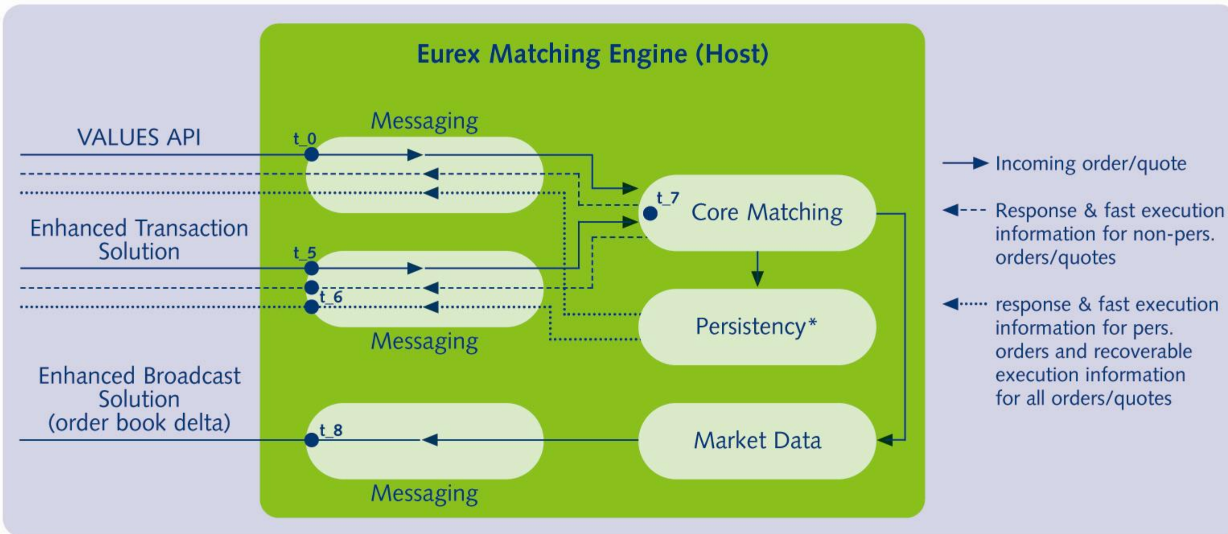
**Choice #6: Avoid seasonal effects**. Predatory algos exploit humans' inclination for seasonal habits, such as end-of-day hedges, weekly strategy decisions, monthly portfolio duration rebalances, calendar rolls, etc. Seasonal effects are easily predictable and are a favorite of HFT algos. Smart LFT trading will avoid these easily exploitable seasonal habits.

## CONCLUSIONS

HFT is here to stay. The current speed advantage will gradually disappear, as it did in previous technological revolutions. But HFT's strategic trading behavior, executed by automated systems interacting directly with the exchange's double auction order book is more robust. Strategic traders have little trouble in adapting to new rules of the game. "Big data" allows them to train their algos before deployment. Advances in machine learning and microstructure theory will compensate for the loss of speed advantage.

Part of HFTs success is LFTs reluctance to adopt the volume-clock paradigm. However, LFTs are not completely defenseless against HFTs. Whenever a new predator makes its appearance in a habitat, there is a shock period until the hunted species adapt and evolve. There is a natural balance between HFTs and LFTs. Just as in nature the number of predators is limited by the available prey, the number of HFTs is constrained by the available LFT flows. Rather than seeking “endangered species” status for LFTs (by virtue of legislative action like a Tobin tax or speed limit), it seems more efficient and less intrusive to starve some HFTs by making LFTs smarter. Carrier pigeons or dedicated fiber optic cable notwithstanding, the market still operates to provide liquidity and price discovery – only now it does it very quickly and strategically.

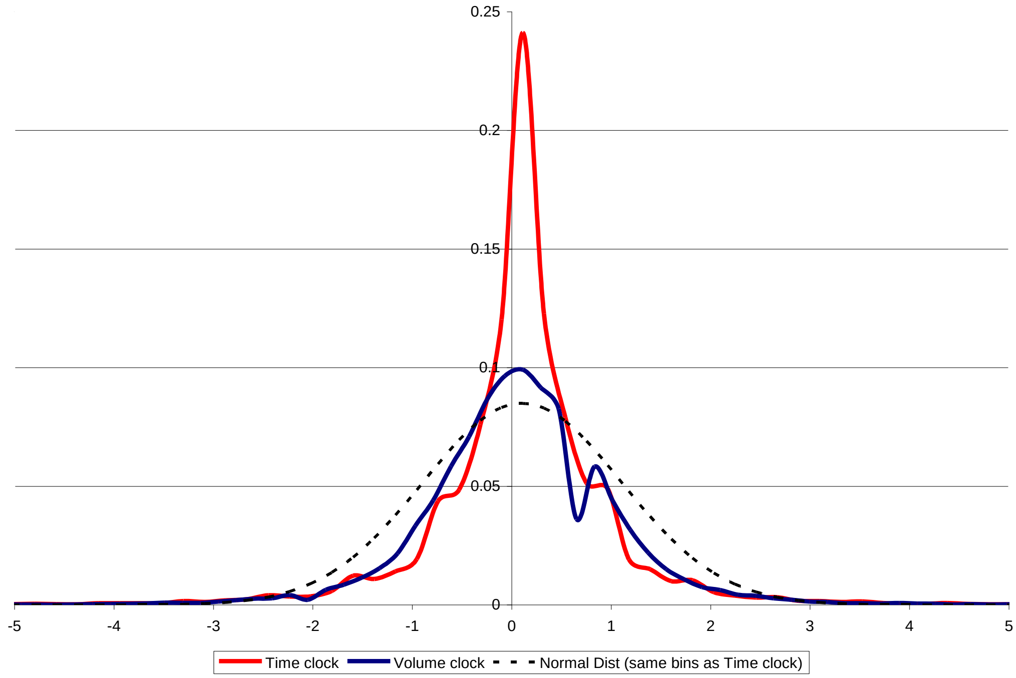
**Exhibit 1 – Simplified depiction of a Matching Engine's host**




* Additional time stamps are available in messages from the persistency layer.

Prices and volumes are determined by the matching engine. HFTs study its design very carefully, in an attempt to uncover a structural weakness in the double auctioning process. Eurex has been particularly transparent in describing its architecture and functionality, in an attempt to level the playing field across customers.

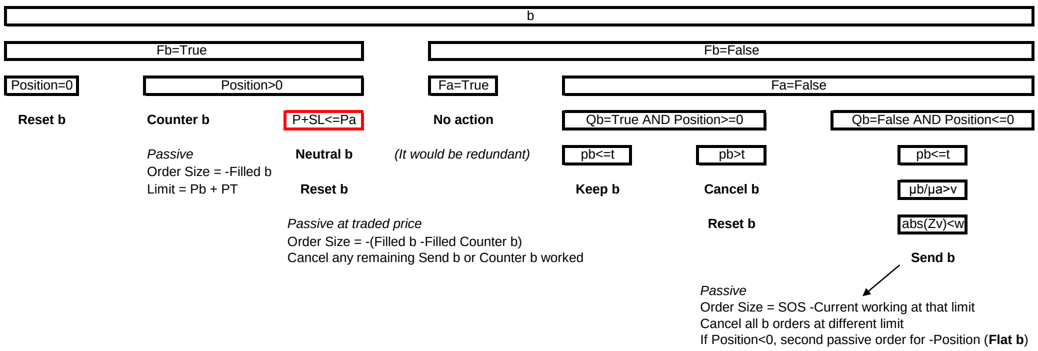
**Exhibit 2 – Partial recovery of Normality through a price sampling process subordinated to a volume clock**

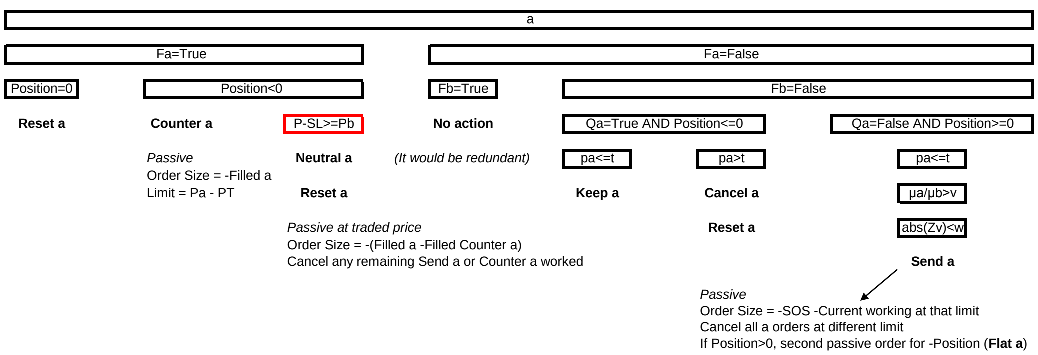



The red line is the distribution of standardized price changes for the E-mini S&P500 futures when we sample every minute. The blue line is the equivalent if we sample every 1/50 of the average daily volume. The black dashed line is the standard normal distribution. The sample goes from January 1st 2008 to October 22nd 2010.

# Exhibit 3 – Example of a Tactical Liquidity Provision algorithm

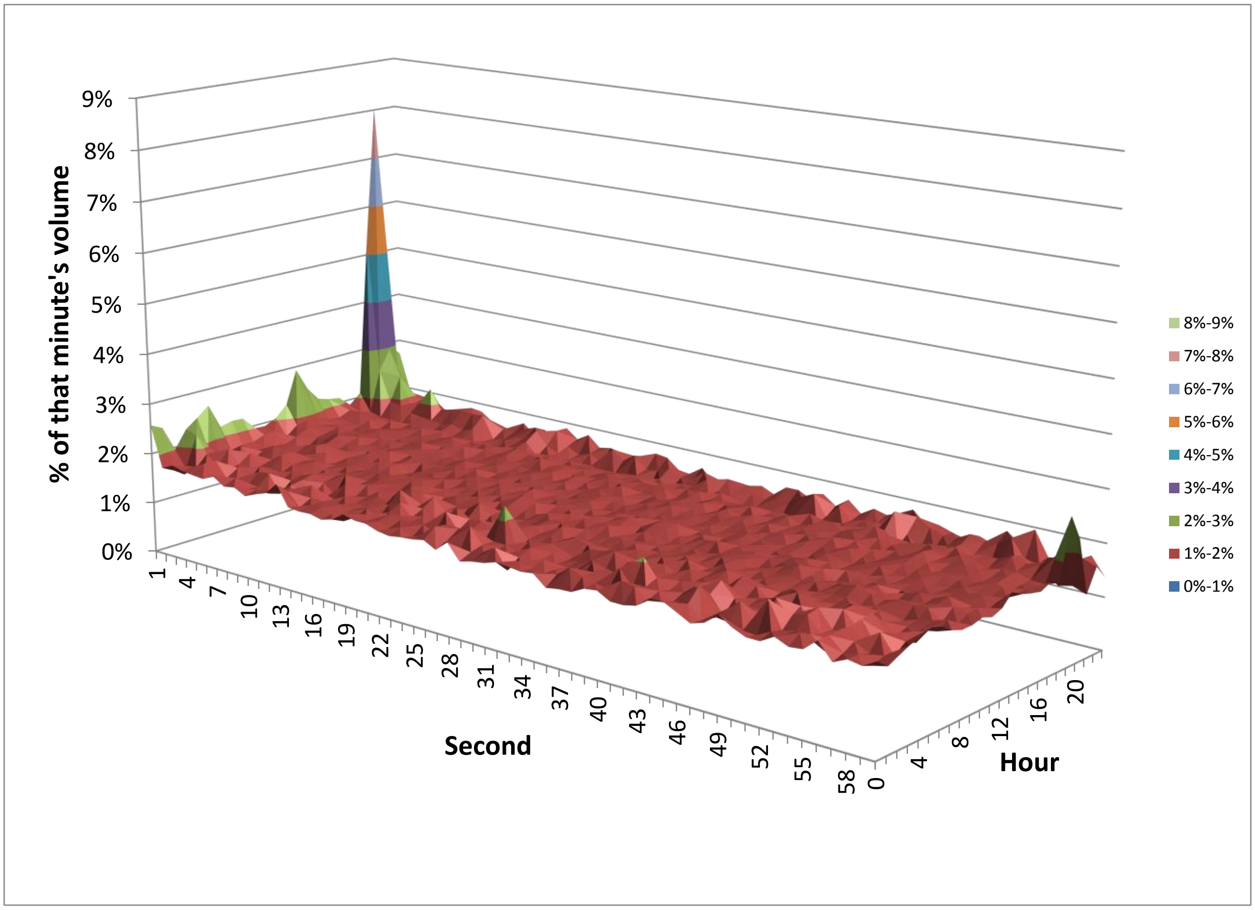
pb:= Probability of bid to be crossed (1 if already crossed)
pa:= Probability of ask to be crossed (1 if already crossed)
Pb:= price filled for Send b
Pa:= price filled for Send a
Zv:= zScore on Volume buckets
t=(0,1):= Threshold on Collapse Probability
v=2:= Threshold on Volume ratio
w=1:= Threshold on Volume Z-Score
SOS=1:= Standard Order Size
SL:= Stop Loss for single Send order
PT:= Profit Target for Send order
Fb=(True,False):= bid was filled
Fa=(True,False):= ask was filled
Qb=(True,False):= bid in queue
Qa=(True,False):= ask in queue




This algorithm would send an order at the bid (b), wait for a passive fill (Fb=True) and only then send an order at the offer (Counter b). At all times the probability of an adverse change in level is monitored (pb). However, if the order at the bid has not been filled yet (Fb=False) by the time there is an increase in the probability of adverse level change (pb>t), then the algorithm cancels the order (b). This is a typical sequential trading algorithm that conditions the provision of liquidity to a limited number of scenarios. In fact, it becomes a liquidity consumer from time to time: If the order got filled (Fb=True) and the level drops beyond a certain stop loss threshold (SL), the algorithm competes for liquidity (box in red).

**Exhibit 4 – Percentage of E-Mini S&P500 futures volume traded at each second of every minute**




LFT's decisions are typically made in "chronological time", leaving footprints that can be tracked down easily. The surface above shows a large concentration of volume (over 8%) traded in the first second of every minute around the close of U.S. equities. Because HFTs operate in "volume clock", they can act as soon as the pattern is identified and anticipate the side and sign of LFTs' massive orders for the rest of the hour. Most academic and practitioner models have been devised in "chronological time", which means that their implementation will lead to patterns that HFTs can exploit to their advantage.

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