The development of a viable class of algorithms for trading in rates and currency markets

Setting the path for a renewed industry to tread responsibly

Abstract: Algorithmic trading is a high percentage of the trading business in developed markets because of the convenience and advantages of price discovery and market depth it offers to institutional and retail participants. The commonly ascribed ills of Algorithmic trading, referred in popular literature as High Frequency Trading led to many negative shocks on the Wall Street including the Facebook IPO and the Flash crash of May 2010, however in other institutional markets like rates and currency there is no reason for global participants to hold back. A new regulatory framework is also being assuaged for Algorithmic trading to be institutionalized in Rates and Currency markets

Introduction

The advent of Algorithmic Trading, known in popular literature as High Frequency Trading has caused much real consternation and debate. It has however, become the backbone of Trading businesses and has changed the experience map for all retail and institutional participants in asset classes from equities to commodities, Foreign currency and all Fixed income markets in Cash or Futures and Options or other derivatives.

The early algorithms applied in Trading were soon accelerated in the creation of a new stylized business of High Frequency trading where market participants benefitted from the liquidity but the almost vertical arbitraging of all assets and an unregulated dispersion thru the industry wreaked havoc on Wall Street including the infamous “Flash Crash” of May 6, 2010. While keeping that in mind, the author(s) would focus in this effort on making possible new classes of algorithms being used as we speak and assuage a viable framework for the global institutionalizing of algorithmic application of technology to harness profit from financial assets, focusing on the more global and liquid Foreign currency and Fixed income markets.

This paper reviews existing literature on the forming subject area and review a viable framework for the new institutional addition to Investment Banking business as a new regulatory framework is created around it to add reliability and long run stability to earnings of bank trading desks and other retail and institutional participants at exchanges for financial assets.

Overview

Available research into the phenomenon of High Frequency Trading and its rise thru the field of Quantitative Finance and Algorithmic Trading show machines that now make 70% of the trades in the US market and more than 33% of the trades in Europe and more than 12% even in Asia, have not really come about at the expense of retail investors but offer real advantages in price discovery and market depth.

Kirilenko and Lo (2013) summarize the underlying developments in the field of Finance and the technological imperatives that led to the growth of the field from an almost 0 share in the 90s to a complete domination of the markets in 2009 on the NASDAQ while we get into a global discussion on the required changes in regulation.

Change is not directed towards improvements in trading. While changes have necessarily been caused by the advantages of speed and volume created by High Frequency Trading in all asset markets including equities, currencies, fixed income and other, market participants have repeatedly erred by creating adverse selection on the supply side while reinforcing price discovery in liquidity demanded (Brogaart, Hendershott & Riordan, 2014).

Even in dark pools, large institutional orders have disappeared in favor of repeated smaller orders (Buti, Rindi & Werner, 2011) but the privacy offered by these private institutional markets is a key advantage for institutional traders. In institutional markets and in retail adverse selection has also increased concurrently with the advantages proffered by AT traders in the less liquid side of a trade, but employment of an AT/HFT mechanism to take advantage of the speed of trading and keep institutional identities private will remain de rigeur even as retail markets like NASDAQ battle with the impact of an undone fiasco or two including the delay during the Facebook IPO in 2012 and the flash crash of 2010.

Overall, we are quite satisfied that Algorithmic trading is here to stay and will be key to trading macroeconomic news creating liquidity and depth at best quotes (Schlotus, van Dijk and Frijns, 2006) and also increases institutional trading efficiency on spreads and short term volatility in liquid assets as evidenced in Dark pools till 2009. A review of the literature also finds that humans ultimately act as "informed" traders in these markets and without human intervention the efficiency in trading news or price arbitrage is not really possible and we investigate if both can indeed live together in a viable market construct.(Chaboud, Chiquoine, Hjalmarsson and Vega, 1999)

We rely on Kirilenko and Lo (2013) and Creamer and Freund (2009) for a reliable history of the work in developing the field of Algorithmic Trading with the use of Expert systems and agent based models culminating into its transformation as the High Frequency trading juggernaut, fighting for each millisecond in speed but creating business in volumes that underlie its basic robustness.

We also review the contribution of High Frequency Data to the field of Finance theories and the basic tools available (Engle and Russell, 2010) and the new tools and techniques in use (Engle and Lange, 2001; Easley, de Prado & O'Hara, 2012; Bollerslev & Todorov, 2011)) to arrive at a probable set of algorithms for further research in the coming year(s) evidencing the application of machine learning, GARCH, Wavelet and Artificial Neural Network models with or without Perceptron and Psi-Sigma Networks while reviewing pairs trading techniques and current research on algorithms to activate consistent profits in foreign exchange and bond markets speculation and recommend Kissell, 2006 for a framework to review and test Algorithmic trading strategies

Interaction with Humans

High Frequency Trading (HFT) or machine induced trading has earlier been studied for direct interactions with Low Frequency Traders (Cvitanic & Kirilenko, 2010)and Informed Traders (Chaboud et al., 2009) Early studies in the 1990s and prior to that from primary authorities in the area proves that machine driven trades are higher serially correlated . Trade during Macroeconomic releases is highly profitable and includes biting trades by informed traders allowing faster price discovery of private information held by insiders or "informed traders" including strategic order splitting to reduce market impact by creating in each trade non informational increase in liquidity

In Foreign exchange markets (*ibid.*)it was first shown that the impact of macroeconomic news is aided and liquidity providers are not passive with the non algorithmic order flow accounting for more of the variance thus showing that HFT traders have evidenced smaller short term volatility while increasing liquidity in the trades since its early days though it does show that algorithmic trades induced into such news streams by HFT are not as diverse as strategies that would be employed by humans/Low Frequency Traders/informed traders

Cvitanic and Kirilenko (2010) study Low frequency buy and sell orders as iid Poisson sequences and in a liquid market demand in the electronic limit order market evidenced by buy orders is similar to the quantity on sell orders that traders are willing to supply in a single trade. The distribution of transaction prices with the presence of a high frequency trader is indeed found to have lesser fat tails, the machine strategy managing to snipe away 'human' orders far from the center (front of the book) and making more profits as the frequency of human trade inputs increases and inter-trade duration is controlled by the rate at which human traders provide quotes. Thus it also seems that HFT trading machines cancel their unexecuted trades immediately to avoid being sniped by other HFT traders and use these quick canceling orders to test the front of the book ("pinging") and carry home more transactions than low frequency traders

Our paper also follows Cvitanic and Kirilenko (2010) in that we stay away from stylized models trying to find the equilibrium price formation and focus on the impact of transaction volumes, trading mechanics and transaction times in the presence of HFT traders

Chaboud et al. (2009) considered a dataset of three currency pairs, EURUSD, USDJPY and EURJPY between 2006 and 2007 in EBS covering most of the global spot interdealer market and found that the HFT traders strategies in these data can be isolated as more correlated but leading to lower market volatility. It is shown in later research that the increase in volatility is caused by another complement of HFT traders that indeed provide passive orders and can be isolated as "bad examples" for regulators and market counterparties as this set of traders increase adverse selection on the opposite side of the liquid trade (a low priced sell order while buying in the front of the book) . The original experiment (*ibid.*) studied the release of the US NON farm Payrolls report and while computers continue market making except at the precise time of the release, and revert to uninformed liquidity supplying quotes, they are able to capitalize on the news in catering to informed quotes driven human "makers" . The volumes transacted by "takers" both human and computer show that while human human transactions dominate Euro Dollar and Dollar Yen volumes, the computer computer transactions dominate the triangular Euro-yen trade thus showing how HFT traders could capitalize on complex triangular arbitrage opportunities in any market while focusing on the direct "sniping" of information filled human trades. Chaboud et al. (2009) simultaneously examine the popular supposition that this higher serial correlation between HFT traders is because of poor design thought and exaggerates market movements on the same side and shows vide an example of August 16, 2007 that while that possibility indeed exists, it is mostly preexisting volatility that is induced as computer "takers" follow human traders in each trade exonerating Professional trading communities of Hedge Funds and commodity trade advisors in the process. As was also found in the popular press in 2012 during the Facebook IPO delay , the systems are at risk because of more antiquated practices and "hard code" following open market regulation such as Regulation NMS of 2005 and MiFiD of 2007 in linking exchanges and allowing theoretically more pricing freedom even in fragile equity markets

Trading on News

The existing body of literature showing mostly congruent results on the characteristics and impact of HFT Traders (Computers/Algorithmic trading/HFT) on trading in currency and other asset markets on macroeconomic news releases, building market depth, liquidity and reducing short term volatility. The first seminal work on the same is attributed to Hendershott, Jones and Menkveld(2007). The work of Peter Hoffman(2014) also formalizes these empirical analyses into a stylized model showing the difference between fast traders and slow traders, similar to Kirlenko

Schlotus

Brogaard, Hendershott and Riordan (2014)

Key Tools and Strategies for employing, mastering and avoiding pitfalls in HFT Trading

The peculiar and heavily weighted one sided characteristics of a HFT Trading/ Algorithmic Trading (AT) market superstructure imply a supposition in popular literature that the advantage of HFT /AT is from speed of execution. Easley, de Prado and O'Hara (2012) show that the 'cheetah traders' build upon the speed advantage licensed unto Financial markets by unified regulation in the US and Europe in 2005 and 2007 respectively as mentioned above. The pricing in these markets is driven by adverse selection and the information asymmetry evidenced in the market microstructure. Strategies being diverse for different asset classes, the commonality of speed is in the implementation of repeatable strategies and hence the predilection for closing out trades by the end of the day on both sides.

The information ratio thus gleaned, advantages concurrent research in market microstructure theories that greatly reduce the uncertainty associated with price discovery in a HFT world. Researchers like Engel (2010) and Easley, de Prado and O'Hara (2012a) lead participants and researchers to the other critical to success parameter of HFT. This Critical to success parameter is indeed apart from Speed and programmatic efficiency, a whirlwind of volume created by the nature of the HFT strategy in employ. Easley et al(2012a) help organize the new market along a new paradigm or two in consequent research, this paper (*ibid)* creating a parameterization of event based time or a discretized time sequence, artificially created out of buckets of time spanning equal contracts (N contracts or n share buckets). Engle and Russell(2010) introduce discretization of time intervals in a handbook on Econometric tools and techniques. High Frequency data is thus employed is Price Discovery Research literature as well to empirically deduce viable strategic alternatives for Pricing assets and trading profitably.

Trading in non-asset debt markets in Fixed income and Currency, rudimentarily more than trading in equities and related derivatives, employ trading in spreads, which has also historically traded in price discovery hidden in the microstructure. An early reference work for example, Engle and Patton (2004), use log difference in bid and ask prices to show buys working for the ask price in a trade and sells work for the buy price in the trade for the same security. Event based time definitions, predate the phenomenon of High Frequency Trading but the strategy allows researchers and traders to ignore equal treatment of different trade sizes in similar time windows and equalization of the trade requirements . Results show that volume is as critical to measuring the minutae that becomes critical in a HFT trading algorithm .

A comprehensive Literature Review on such trading strategies is pending and a selection of empirical research referencing Artificial Neural Networks, Wavelets, Kalman Filters and machine learning techniques like Alternative Decision Trees and Irreversible Reinforcement Learning is included in the references and in Amit Mittal (2014) apart from many references in application by industry insiders. Evolutionary Algorithms on the other hand allow treatment of customized objective functions that do not respond to mathematical strategies and have traditionally incorporated use of one or multiple machine learning strategies.

Easley, de Prado and O'Hara also critically introduce a concept of Flow Toxicity to measure the adverse selection presented by the overpowering memes of programmatic trading. While all Algorithmic Trading and employ of Genetic algorithms is not HFT, All HFT requires AT and is thus dependent even in spread based markets in Currency and Bond markets on the asymmetric towers in double sided auction trading.

A recently popular strategy among HFT traders involves using trading in Odd lots to facilitate price discovery in hidden corners of the market allowing the trader to not reveal himself or his business requirement. O'Hara, Yao and Ye (2009)

Show that 35% of the price discovery can be explained by Odd lots, and the strategy is used by human or informed traders in programmatic leaning markets as well. Odd lots being 60% of transactions in key securities (though the evidence is readily gleaned only in equity markets) the compensation for the same by HFT trading strategies is paramount for fairly operating public securities markets. Finally, Flow toxicity measures, introduced by Easley et al(*ibid,2012b)* and promoted by Hendershott and other researchers use information in Probability of Informed Trading (PIN; VPIN) measures proposed by Easley et al. (2012b) as also the Volume Clock meazsures(Easley et al, 2012a) to execute trading strategies that advantage from HFT traders' following information rich trades from Low frequency traders.

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