OULU BUSINESS SCHOOL

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EVALUATING PERFORMANCE CAPACITY OF HIGH FREQUENCY TRADING STRATEGIES, BASED ON COMPARATIVE RATIOS AND MARKET INEFFICIENCY AT HELSINKI STOCK EXCHANGE

Master's Thesis

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ABSTRACT OF THE MASTER'S THESIS UNIVERSITY OF OULU

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Abstract:

High frequency trading is not only about the speed but also about the effective trading strategies it uses to perform the trade. Performance capacity evaluation of high frequency trading strategies is done using different comparative ratios. Studies find, due to tight spread, it is difficult for high frequency traders to generate significant alpha by trading the highly liquid stocks using market making strategy. But they can still generate positive return with Sharpe ratio almost equal to market. They act more like market makers following this strategy. The capacity of other high frequency trading strategies lies in between (58-75) %. Statistical arbitrage strategy is the best among all the high frequency trading strategies. Sharpe ratio as a main tool of comparison between high frequency and non-high frequency traders, shows multiple times higher Sharpe for high frequency traders in comparison to non-high frequency traders. Value at Risk (VaR) suggests the probability of generating positive return for all the strategies having long and short positions.

This thesis takes one month high frequency limit order and tick data from NASDAQ OMX Nordic and select six mostly traded Finnish stocks based on their limit order book activities. Basic limit order book activities of all the selected stocks is analyzed including and excluding non-high frequency activates to make sure all the selected stocks are influenced by high frequency activities, so that the result is more accurate. This thesis follows the high frequency trading strategies and respective holding periods suggested by Aldridge (2009). Sometimes strategies work not because strategies are efficient but due to market inefficiency. This thesis crosschecks the market inefficiency with autoregressive based test. Due to tick data and a very short time interval between the two observations, it finds strong influence of past returns and past price movements in the current return suggesting inefficiency in the market.

Keywords: High Frequency Trading Strategies, Limit Order Book Activities, Comparative Ratios, Performance Capacity Evaluation, Autoregressive Based Test of Market Inefficiency, Value at Risk (VaR)

Additional Information:

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Niranjan Sapkota
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1. INTRODUCTION

Trading, over the last decade has gone through a dramatic shift with the radical improvements in technologies. Floor Trading[1] has been replaced by computerized trading platforms. Limit orders can be set at a certain level of price and the order is executed as per the types of orders. Traders now either have to sit in front of the computers or write complex algorithms with pre-specified strategies to make orders.

Machines are replacing humans with built in artificial intelligence and complex algorithms. Machines can now react to the current news and take anonymous decisions. Earlier, machines were supposed to perform technical analysis on the asset price movements and speculate the upcoming trends but these days, machines can perform fundamental analysis also with more effectively and efficiently than a human. Computer generated automated trading is increasing by huge numbers every day. Improvement in electronic communication and processing system makes it easier to make orders.

Supercomputers can now generate millions of orders in a millionth fraction of a second. One second is a very long time interval for high speed traders. Milliseconds[3] and Microseconds[4] are the new time horizon for those high speed traders. Orders are generated, cancelled and executed in a tiny fraction of second and this type of trading pattern is called the High Frequency Trading (HFT, here onward).

HFT refers to fully automated trading strategies in different securities like equities, derivatives and currencies. HFT traders seek profit from the short-term pricing inefficiencies. These types of opportunities have life span from milliseconds to minutes. Capturing a tiny fraction of cents from each trade in huge number makes HFT an efficient way to generating money. Holding period of the securities is usually less than a minute but depending upon the strategies and the market situation it can be hold till the end of the trading day. The holding period of non-HFT orders can be more than a month depending upon the types of strategies used. Sometimes holding period can be based on the types of investors where individual investors' holding period can be shorter than the institutional investors and vice versa.

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[1]Floor trading is where traders or stockbrokers meet at a specific venue referred to as a trading floor or pit to buy and sell financial instruments using open outcry method to communicate with each other. [2]One thousand milliseconds= one second, [3]one million microseconds = one second

The idea behind this thesis is to study the performance capacity of different HFT strategies based on the comparative ratios as suggested by (Aldridge, 2009) in the context of Finnish stock market. HFT in Finnish stock market is also in increasing phase. Around 25% of the trades are generated by HFT in OMX NASDAQ Helsinki Stock Exchange (OMX NASDAQ, 2013).

In today's fast moving world the transfer of information from one place to another is in the speed of light. Technology is bringing the change in the way of trading of not only the intangible assets but also the tangible assets. People these days are involved in trading to generate high amount of profit from even a small change in the market price. Traders, these days are becoming high profile business people. Along with the development in the trading mechanism, trading is becoming more challenging and risky. Arbitrageurs[4], Hedgers[5], and Speculators[6] are facing lots of challenges to convert market information into profit. Since, these days market is supposed to be efficient. Price reflects all the available information. Traders takes the advantages of information asymmetry, but since, market is efficient, they have to set some strong strategies which leads them to a huge amount of profit. Sometimes the same kind of strategies works all the time, but this is because of the inefficient market. Thus, the main motive of this thesis is to cross check the market inefficiency along with examining the performance capacity if HFT strategies.

Aldridge (2009) has suggested an autoregressive based measure to capture the market inefficiency. Restricted auto regression suggests that there is no lag dependency between the lag returns, thus the price reflects the current available information, whereas, unrestricted auto regression suggests that the current return is the outcome of past returns, thus there is lag dependences between the lag returns. Market efficiency takes into account, both the aspect of price dependencies. HFT Strategies are the tools designed by the joint knowledge of finance professional, mathematician, programmers and many other people. There is no certain specific strategy. New strategies come as an innovation in financial market.

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[4]Arbitrageurs are one of the types of traders who make risk-free profit from the inefficiencies in the market in zero cost. [5] Hedgers are the investors who invest in related security to reduce the risk of adverse price movement of assets. [6] Speculators are the risk takers, who trade all kinds of securities by speculating the price movement of the security and make higher potential profit.

1.1 Evolution of High Frequency Trading (HFT)

Market adopted the modern technologies from the early 1970s. National Association of Securities Dealers Automated Quotations (NASDAQ) is the first stock market to introduce electronic quotation system. Later in 1976, New York Stock Exchange (NYSE) introduced Designated Order Turnaround (DOT) system to generate buy and sell orders of the securities. Computerized trading came in 1980s where small numbers of securities were traded using different trading strategies. After Electronic Communications Networks (ECNs) were established, electronic trading became wider (McGowan, 2010). Floor based trading is replaced by electronic platforms. Traders can place orders from anywhere if they have subscription to electronic trading platform. In 1990s computer generated automated trading system gained huge popularity as it has less manual error with high speed and efficiency. U.S stock exchanges replaced the old fractions price quoting with decimals in 2001, which resulted to minimum spread decreased to 1 cent from 6.25 cents. Due to this huge drop in spread, traders (especially spread seekers) identified alternative approach of trading securities, which leads to the immergence of HFT. Security Exchange Commission (SEC) passed the Regulation National Market System in 2005, improving the transparency and competition between the markets (Agarwal, 2012). After such regulation, exchanges have to post their trade orders nationally but not only at the individual exchanges. Spread seeker can now get the profit from the price differences of the same securities in different exchanges in real time. The radical development in information technology along with the improvement in high-speed information transformation and processing system boosted the High Frequency Trading in today's date. HFT firms can be categorized into three different groups as per their nature;

- **Independent HFT Firms:** These types of firms use private money with different strategies. Usually they remain to keep silent and confidential about their strategies.
- **Broker-Dealer HFT Firms:** It is the traditional form of trading with separate trading desk for HFT traders.
- **Hedge Fund Firms:** They focus specially on quantitative strategies like, statistical strategies to take the advantages of pricing inefficiencies among different assets classes.

In a very short period of time HFT has captured a large portion of US and European stock market. HFT has been increasing in recent days in many Asian countries like, China and India.

2009/10/11 was the peak year of HFT revenue generation. In the recent years, although the large portion of the trading is captured by the HFT firms, the revenue generation pattern and the market share of HFT firms is decreasing in each year. In year 2013, the market share of HFT firms in Europe is around 30% where as in US it is around 50%, though the market share is not so much in speed to decrease but the revenue generated by the HFT firms is decreased by more than double since year 2010. Many HFT firms are expanding their operation in Asian countries seeking opportunities. In 2012, the market share of HFT firms in Asia is about 15% now it is in increasing stage. (TABB Group 2013)

In today's world, everything around is digitalized and they are mobile. Now people can trade from anywhere. Digital gadgets can be carried inside one's pocket, network connection is available almost everywhere. The data connection service provided by the telecom industries is making it easier for traders. It is little bit different for High frequency traders as they need more network speed and strategy processing speed. But, in recent years, mobile gadgets like iPad with huge storage and processing speed is making it easier. HFT firms generally needs higher speed and the proximity with the exchange so that they can implement their strategies before ordinary traders do.

Many European countries are still not involved in HFT. US based HFT firms are expanding their operations in many European countries. Merrill Lynch is active in NASDAQ OMX Nordic Exchange. HFT firms usually focus on equity market, but due to very low spread and higher market efficiency in equity market, nowadays HFT firms are involved in foreign exchange, commodities, global fund and fixed income securities.

Many developing nations are still far behind of HFT. This is because HFT needs highly sophisticated modern technologies. Some countries are still following traditional ways of broker, dealer equity trading mechanism. The more human the intervention the less is the possibility of HFT to take place. Lack of knowledge on HFT is also another problem in establishing HFT in many developing countries.

1.2 Finnish Stock Market

Helsinki Stock Exchange (HSE) was founded in 1912 as a nonprofit cooperative organization but later in 1995 it was reorganized as a Limited Liability Company. In 1997 Helsinki Stock Exchange and Finnish Option Exchange were merged and formed Helsinki Security and Derivatives Exchange Limited, also known as HEX Limited, (Bank of Finland, 2003).

Today Helsinki Stock Exchange is the part of NASDAQ OMX Exchanges. OMX operated stock exchanges in Baltic and Nordic countries. In 2007 OMX merged with NASDAQ (American technology stock exchange). In today's date NASDAQ OMX operates stock exchanges in United States and Europe including Nordic and Baltic nations. It has 70 stock exchanges and clearing houses in more than 50 countries. (porssosaatio.fi, cited 2010).

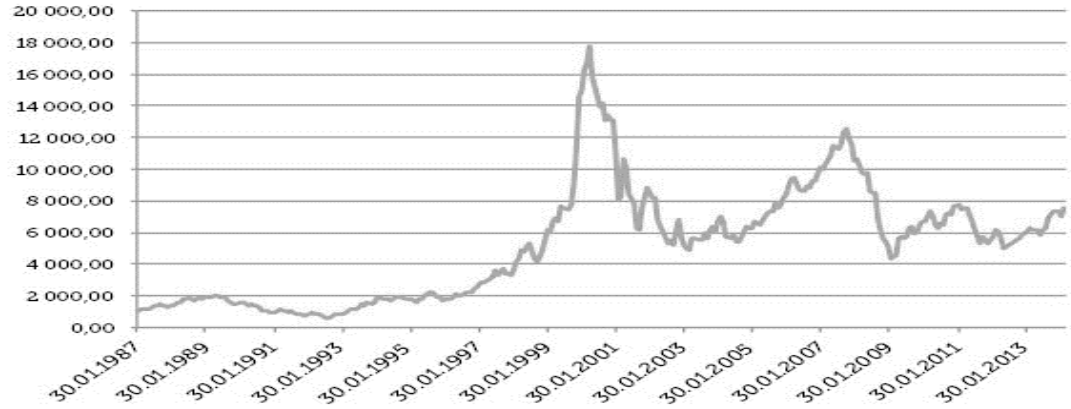

Figure 1: ***NASDAQ OMX Helsinki Stock Index (1987-2013, Source: NASDAQ OMX Nordic)***

NASDAQ OMX Helsinki Index has its highest index value in year 2000/1, now the index is again growing after the economic recession of 2008. Finland is not touched so much by the economic depression of 2008 but since, it has listed many other international stocks, which decreased the index value of NASDAQ OMX Nordic. The technical and infrastructural development in NASDAQ OMX Helsinki Stock Exchange has been developed radically in these recent years. The automated and real-time trading system which was introduced in 1989 is now more accurate and faster.

For detail information about the corporate timeline of NASDAQ Exchange, go through this link: http://www.nasdaqomx.com/aboutus/company-information/timeline

Liberalization and Deregulation has strong impact in Finnish financial market in recent two decades. Foreign investors are free to invest in Finnish market whereas Finnish investors are free to invest in foreign markets. Deregulation has made room for financial innovation which leads to the identification of alternative investments and other measures of risk management. Finland is now the member of European Union and with the economic integration with European Union and around the world has increased the efficiency of both the investors and the financial market.

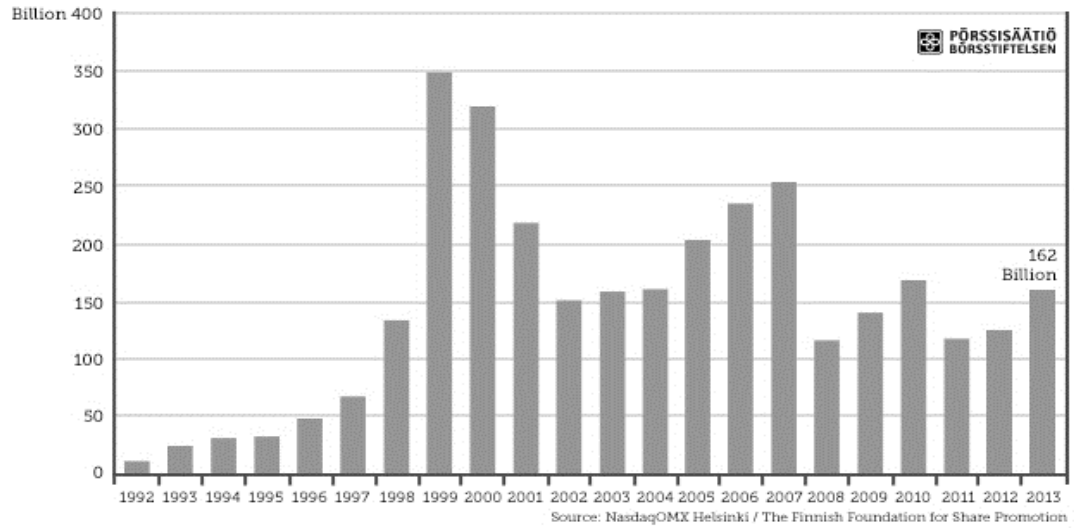

Figure 2: ***Market value of NASDAQ OMX (1992-2013, Source: NASDAQ OMX Nordic)***

After year 1999 the market value of NSADAQ OMX has been decreased and the market value now is still lower than what it was in year 1999. This might be the effect of Dot-com Bubble[7] from year 1997-2000. Finnish stock market is supposed to be untouched in the financial crisis of year 2008 but the market value of NASDAQ OMX Helsinki is clearly seems to be fallen over by half.

The market value of NASDAQ OMX Helsinki is year 2013 is around 162 Billion. New evidence shows that the value of Helsinki stock exchange has been rising consistently since year 2011. Though the increment in the stock prices is not significant to come to the pick level in comparison to the previous decades. The market value of the exchange is just a little bit higher than its peak value in year 1999.

[7] Dot-com Bubble is also known as the internet bubble during late 1990s, where the equity markets' value was increased by the investment in internet-based companies. In this period the NASDAQ index raised from under 1000 to 5000.

1.3 High Frequency Trading in Finland

HFT in European market is in increasing phase. According the data on European stock market, NASDAQ OMX reveals that that the HFT activities in NSADAQ OMX Nordic (Sweden, Denmark, Finland) has been doubled in year 2011 to year 2010 from 6.5% to 12%. NSADAQ OMX Nordic's HFT activities is increased almost by double to 170 billion euro in year 2011 from year 2010 where the overall market activities including HFTs and non-HFTs is increased by 5% to 1.4 trillion euro. Ctiadel Securities is the biggest HFT firm in NASDAQ OMX Nordic. Here are some of the biggest HFT firms active in NASDAQ Nordic,

- Citadel Securities (Market making division of Chicago-based hedge fund)
- Spire Europe (a spin out of US hedge fund Tower Research Capital)
- Getco Europe (European arm of Chicago based hedge fund)
- Virtue Financial (Acquisition of Madison Tyler)
- Susquehanna (Bank and financial institute active Mid-Atlantic region)
- IMC (German Based Trading Firm)
- Optiver (German Based Trading Firm)

Where the most active HFT firms in Finnish stock market are;

- Merrill Lynch (Largest brokerage firm in the world combined with Bank of America)
- Skandinaviska Enskilda Banken AB (SEB) (Swedish financial group for corporate customers)
- Deutsche Bank AG (German global banking and financial services company)
- Deutsche Bank London Branch (DBL)
- Avanza Bank AB (AVA) (Swedish Bank)

Merrill Lynch is the top most active member in Finnish Stock Market as well, responsible for around 14% of the stocks trading. Following the combination with Merrill Lynch, Bank of America has become the largest brokerage in the world, with more than 15,000 Financial Advisors and approximately $2.2 trillion in client assets. A leading provider of global corporate and investment banking services, including commercial lending, global high-yield debt, global equity and global M&A and a global leader in wealth management, private banking and retail brokerage

(www.ml.com). First North is the NASDAQ OMX's European growth market created for all small and growing firms. First North provides these growing markets more room using less extensive rulebook than the major market. First North companies have the advantage of being listed and they can focus of their growth. Every major company listed in exchange were first part of the First North at the very beginning. To be assured about the growth companies are following all the rules and regulations of the exchange, a Certified Adviser is assigned to each and every companies under First North group.

	Value millions		No. of trades		Market cap billions
	Average November	Average past 12 months	Average November	Average past 12 months	end of Nov 2013
Stockholm	11 137	12 089	171 906	183 399	4 734
Helsinki	369	379	65 279	67 494	162
Copenhagen	3 602	3 016	61 133	55 207	1 608
Other	6.8	6.8	519	632	8.3

Most traded companies	Daily turnover, MEUR		**Most active members in share trading**	Market share by turnover	
Large Cap	**Nov**	**Oct**	**Large Cap**	**Nov**	**Oct**
Nokia Oyj	107.8	143.8	Merrill Lynch	13.9 %	14.2 %
Nordea Bank AB	99.0	102.0	SEB	7.5 %	6.6 %
Novo Nordisk A/S	80.8	81.3	Deutsche Bank	6.7 %	5.6 %
Mid Cap			**Mid Cap**		
Genmab A/S	7.0	4.5	SEB	10.8 %	10.7 %
Cloetta AB	6.5	0.5	Carnegie	8.7 %	6.5 %
Eniro AB	3.9	1.3	Danske Bank	7.5 %	6.5 %
Small Cap			**Small Cap**		
Arcam AB	7.5	5.4	Avanza	18.7 %	20.3 %
Fingerprint Cards AB	7.2	10.8	Nordnet	15.6 %	16.1 %
Orexo AB	2.5	2.2	SEB	10.2 %	10.7 %
First North			**First North**		
Africa Oil Corp.	8.8	8.3	Avanza	20.8 %	23.4 %

Table 1: ***The Most Traded Stocks and the Most Active Members (Source: NASDAQ OMX Nordic)***

NASDAQ OMX is the only exchange that reveals the level of trading activities of its members. Which show the growing influence of US-based firms in European market. There are less Finland based HFT firms but more US based and other investment banks outside Finland. The most traded stocks include Nokia, Nordea, Nova Nordisk, Metso, Estora Enso, Outokumpu, etc. NASDAQ OMX HEX is a limit order book market with the trading system called HETI (Helsinki Stock Exchange Automated Trading and Information System) similar to other limit order book market (LOB).

Liquidity is provided on the basis of trade price and the time of order submission. The content of the limit order book market is shown in the trading platform of all the members of the exchange, therefore HETI is very transparent. In HETI system, description of orders and its submitter is displayed individually on the trading platform. In LOB the orders submitted from the dealers or the individual investors are treated similarly without any differentiation since the dealers do not have any compulsion in providing liquidity. HETI follows continuous trading and the liquidity is provided by the outstanding orders in LOB. In some LOB markets only limit orders are considered in HETI system. Limit price cannot exceed the best price level. Order matching is done for each and every order in different price levels. High Frequency Trading in Finland started gaining its popularity after the financial crises of 2008. In today's date around 25% of the stock trades are made by HFT.

Figure 3: ***HFT in NASDAQ OMX Helsinki (2010-2013, Source: NASDAQ OMX)***

The activities of HFT firms in Helsinki in 2013 July decreased drastically because of some amendments in the rules and regulation of HFT because of which many HFT firms had to withdraw their licenses from HFT.

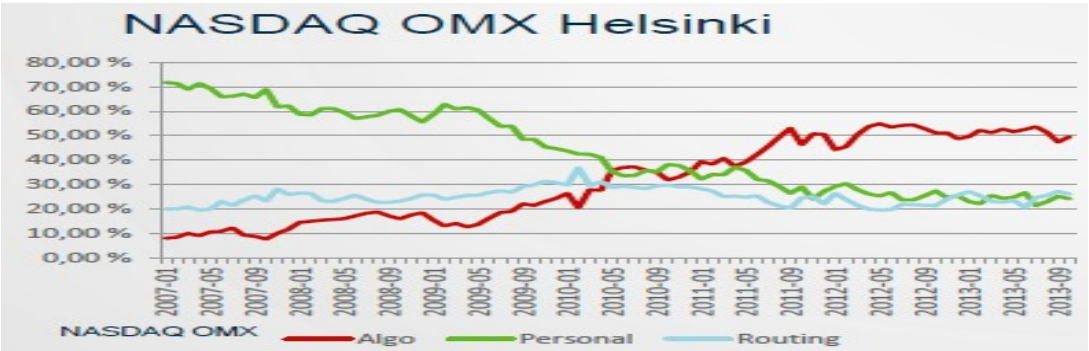

Figure 4: ***Algorithmic Trading in NASDAQ OMX Helsinki (2007-2013, Source: NASDAQ OMX)***

Algorithmic Trading (AT, from here onward) is continuously in increasing phase. In year 2007, the percentage of AT was less than 10% now in year 2013 it has increased up to 50%. Personal traders are decreasing continuously with the increase in AT and

HFT. Personal trading was above 70% in year 2007 and it is less than 20% in 2013. The smart order routing is consistent with time and it is around 25% since year 2007. More than 50% of the total trade done is US equity market is made through algorithm. The large orders are fragmented into different small order size to maintain the balance of trade. Order imbalance can react on price change. Sell side order imbalance and buy side order imbalance are generally seen at the beginning and closing of the trading day. HFT and algorithmic trading is essential to apply quantitative strategies like statistical arbitrage, ETF arbitrage. One of the controversies in HFT is that it provides the trade volume but not the liquidity when needed. Security Exchange Commission has drafted a new law on the regulation of HFT market that firms are not allowed to stub quotes[8]. NASDAQ OMX Helsinki uses the HETI (Helsinki Stock Exchange Automated Trading and Information System). It is a limit order book (LOB) market where every limit order and the identification of its investor are displayed separately on the trading screen. Liquidity of the market is based on the limit orders placed by the individual and institutional investors. Orders are executed based on the price and time of placement. In limit order book market orders are treated similarly either it is submitted by the dealers or the individual traders. The dealers are not obliged to provide either liquidity or any other trading privileges. The immediate liquidity of the market is provided by the limit orders outstanding in the limit order book. The rise of HFT and low-latency trading strategies also making issues on potential market access and the market abuse. There are various quantitative strategies that can be used to capture profit from the low latency but the foremost thing that is important than the effective strategies is the technology that is used to access the market. Skouras & Farmer (2013) explain that the only thing that is most effective in HFT to generate profit is the speed advantages through the co-location of server near the exchange. The one who is in front of the queue is the vital player in the market. Speed advantage and the co-location can be achieved only through the huge financial expenses. Finland- based HFT firms are just in startup phase with less amount of capital it is quite challenging to co-locate their server competing with US-based hedge funds giants.

[8]Stub quotes are used by trading firms when they do not want to trade at certain prices level and want to ensure no trades occur. Firms will offer quotes that are out of bounds. They place stub quotes when there is a liquidity problem.

1.4 Motivation for Selection of Topic

There is always one dominant player in HFT who gets the news feeds micro seconds sooner than the competitors. There are so many HFT firms active in the market. All may not use the same strategy to make profit. There are various strategies that optimize the value of HFT strategies; most of them are highly dependent on ultra-low latency. To realize any real benefit from implementing these strategies; a trading firm must have a real-time, collocated, high-frequency trading platform-one where data is collected, and orders are created and routed to execution venues in millisecond times. It is really quite easy being super-fast but it is very expensive and hard to become the fastest. There is a huge difference between price and speed, for example there are specific HFT data feeds between Chicago and New York that cut latency about 50% (from 16 to 8milliseconds), about 250,000 USD per year. (zerohedge.blogspot.fi, cited 2009).

Analyzing the information available in the order book and react to this before a Goldman Sachs, Getco and others HFT firms can really be profitable but on heavy cost. One does not have to be as fast as one of them; it has to be faster than all of them. Second place will not take us very far in HFT (London School of Economics, 2011).There are so many HFT firms and only one can be the fastest among others in getting news feed. Being fastest is not always possible. It cost huge amount of money and technologies. Writing complex algorithms with effective strategies can be helpful in generating profit. One strategy may not generate profit all the time. Right strategy at the right time is the only way to generate profit. Looking for mispricing and getting profit is not always the case.

Hendershott and Riordan (2009) consider 25 largest HFT firms active in NASDAQ during the year 2008/9 and they found that the statistical arbitrage works almost all the time, making 100% performance accuracy, whereas most of other HFT strategies works at least 51% of times. This paper will check the performance capacity of HFT strategies especially in Finnish stock market. Not focusing on the most active HFT firms but focusing on the most traded stocks by those most active firms.

Although there are so many researches done in HFT strategies, there is still a gap in the performance capacity evaluation of those strategies. This paper will try to fill that gap. Strategies are the technical way to get profit from the investment. They differ as per time and other characteristics of the assets and the firms. Profit from the strategy is time dependent and same strategy does not work every time.

This paper will try to find the time dependency of different HFT strategies in Finnish Stock Market. The capacity of the trading strategies will be evaluated based on the comparative ratios and again cross checked with the market inefficiency. Sometimes strategies seems to be working even if they are not so effective, which can be due to market inefficiency.

Most of the active members in Nordic and Finnish stock market for HFT are the firms that are based on the outside of the Finland. Finland is one of the best technologically advanced nation but still there are not sufficient HFT firms. Most of the HFT activities are done by the firms those are based outside of Finland. This thesis will be helpful to those who are willing to involve in HFT activities in the Finnish stock market and unaware of what strategy is best for Finnish stock market.

Cartea et al (2011) have distinguished two types of market orders as influential and non-influential. This thesis will look for the influence of HFT activities in LOB after excluding non-HFT activities in selected Finnish stocks. Pragma (2012) and Kearns et al (2010) empirically show that profit generated by most of the HFT firms is centered to few highly liquid stocks. We will check either similar situation exists with Finnish stocks or not.

This thesis will be the first paper to analyze the performance capacity of HFT trading strategies in Finnish stock market using comparative ratios and market inefficiency, empirically.

1.5 Research Questions

Since the motive of this thesis is to study the performance capacity of HFT strategies in Finnish Stock market based on comparative ratios, we will find the ratios of different HFT strategies. Strategies are differentiated based on their holding period as suggested by Aldridge (2009). To make sure either they are HFT strategies whose capacity generates alpha or it is because the market is inefficient, this paper will cross check the inefficiency of the Finnish stock market. The main research questions of this thesis are;

- Main Research Question
  - What is the performance capacity of HFT strategies in Finnish Stock market?

  Sub Research Questions
  - Is the Finnish stock market inefficient?
  - Strategies are efficient or the market is inefficient?
  - Does same strategy be profitable for all the stocks?
  - Are HFT strategies, time dependent?
  - Which HFT strategy works better in Finnish Stock Market?
- Hypothesis to be tested
  - HFT strategies are dependent on time and stock selection as profit (α) generated using same strategy for all the stocks for all the time is not statistically significant.

    Null Hypothesis (H_0) $\Rightarrow \alpha=0$

    Alternative Hypothesis (H_1) $\Rightarrow \alpha \neq 0$

The first goal of this study is to explore the hypothesis thorough manner, both through statistical analysis and through proving it using empirical data. Though, Aldridge (2009) has given the basis for measurement of performance capacity of HFT strategies, but no research is found to apply her suggestions empirically. This paper will try to give some empirical evidence to those strategies.

As the argument by Skouras & Farmer (2013), the only thing that is the most effective in HFT to generate profit is the speed advantages through the co-location of server near the exchange not the strategies. This paper will try to find out whether the different strategies used in different times among different stocks are enough to get alpha from the trading or not.

2. THEORITICAL FRAMEWORK

This section, first deals with the definition of key concepts such as HFT, and AT and further explains other related terms of HFT, chosen for this thesis. What are different HFT strategies and how those strategies are evaluated is the main concern of this section. It provides a review to previous empirical studies done by the scholars in HFT and HFT strategies, evaluating HFT strategies, where the most important findings, opinions, and the research gap is discussed as a literature review.

2.1 Definition of HFT

One must be familiar with Algorithmic Trading to understand HFT. AT uses the computer algorithms to make automated trading decisions, submit orders, and manage orders after submission (Hendershott & Riordan, 2009).

Aldridge (2009) characterizes HFT as;

- Short position-holdings (seconds, minutes or hours but less than a day)
- No or small overnight positions
- A large number of trades with a small profit per trade
- Analysis of tick market data

These days the latency of HFT is calculated in microseconds. Seconds is way too long period for high frequency traders. Generally the position which stays overnight is not considered as high frequency activity. HFT is all about the combination of mathematics and technology. Many financial professionals say that there is nothing to do with finance guys in HFT. Since it is all about speed and the complex algorithms to capture market inefficiencies, the built in algorithms can do such analysis which is bringing controversies in HFT.

U.S. Securities and Exchanges Commission attribute certain specific characteristics of HFT and they are;

- Use of highly sophisticated computer programs for placing and executing the orders.
- Use of co-located servers to get individual data feeds from the exchange with very low latency.
- The holding period of the position is less than a second.
- High orders submission but low executions.

The description of HFT in case of Aldridge and U.S Securities Exchange Commission is little bit different in terms of holding period of the securities. U.S Commission takes into account the less than one second holding period as high frequency where Aldridge says high frequency trading holding period can be less than a day as well.

Gomber et al. (2011) states seven common characteristics of AT and HFT, such as; pre-defined trading decisions, use by professional traders, observing market data in real time, automated order submission, automated order management, no human intervention, and use of direct market access.

2.2 Difference between HFT and Algorithm Trading

The best way to differentiate HFT from AT is to understand that, "*All HFTs are ATs but ALL ATs are not HFTs*". There are many similarities between HFT and AT.

	Characteristics	**HFT**	**AT**
Similarities	Automated order submission and execution	✓	✓
	Real-time data	✓	✓
	Direct/sponsored market access	✓	✓
Differences	Order frequency	Very high	Varies
	Holding period	Typically less than a minute but depends upon the strategy.	It can be days, weeks or months depending upon the trade size.
	Latency sensitivity	Extremely high	Varies
	Instruments	Focuses on highly liquid securities.	Varies

Table 2: ***Similarities and differences between HFT and AT (Source: Aldridge 2009)***

It is sometimes difficult to distinguish HFT from AT. To have better concept on HFT it is first necessary to have knowledge on AT. HFT and AT differs to each other in terms of holding period. AT might have holding period more than a trading day where as HFT has no overnight position.

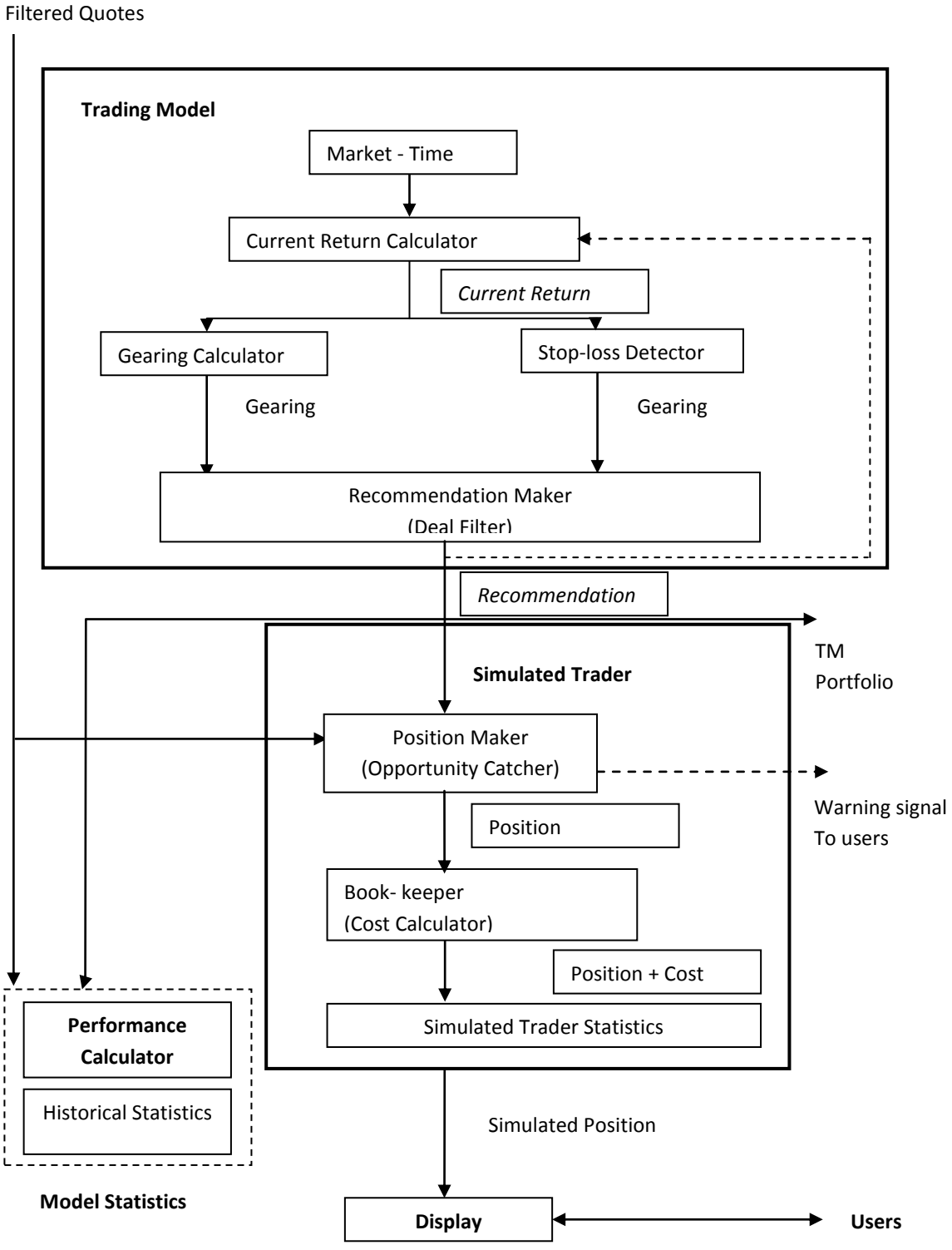

Figure 5: ***Real time trading model with data flow of prices and deal recommendations (Source:*** Gençay ***et al.2001: pg. 298)***

The trading model of any securities largely depends upon the quality of data feed receiving from the exchange. Any applications either it is forecasting or other trading application models can perform better with the qualitative data. Bad or incomplete data can be very harmful to the traders. Real time trading models used the high frequency data feed and reacts to it instantly. Real time trading model is usually high risk and high return model. HTFs are the subset of Real Time Trading (RTT). We can say, *"All the HFTs are RTTs but all the RTTs are not HFTs."* High frequency traders use the real time tick by tick frequency level data. HFT firms use real time trading models to capture the spread and the arbitrage from the pricing error. The real time trading strategy model must have the following characteristics; prior warning mechanism,

- Consistency in recommendations,
- Recommendations within business hours,
- No recommendations in holidays, and
- Real time, stop loss support mechanism.

Based on the pre-determined model, the real time trading model must give recommendations consistently to the portfolio manager. Recommendations have to be within the business hours when there is possibility of trading the securities. The trading model must be pre-programmed about the business hours and the holidays so that it can give recommendations when needed. All the HFT strategies have the capacity of performing real time trading. All the strategies should be able to have real time stop loss mechanism. Profit generating capacity of the strategies can be helpful in generating money but sometimes if the strategies are not built with stop loss mechanism than it might be dangerous to the trading firm. The incident like Flash Crash[9] of 2010 can make the trading firm insolvent if they do not have the stop loss mechanism in their trading strategies. One should be aware of possible loss while thinking about the possible gains. Target limit or stop loss are the tools that always help in retaining profit and saving the traders from big hazards of loss. All the HFT strategies also follow these real time trading principles. HFT strategies are more complicated than the normal real time trading strategies so that they can capture profit in complex and high speed environment.

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[9]Flash Crash is the quick drop and recovery in the price of securities that occurred on May 6, 2010 shortly after 14.30 Eastern Standard Time. Although the security exchange commission report gives several reasons but the real reason is still unidentified.

2.3 HFT Strategies

Market must be highly liquid to apply the HFT strategies. Similar HFT strategies can be applied to different markets like, equities, foreign exchange, futures, options and other derivatives. HFT strategies benefit society in so many ways, such as;

- Increased market efficiency
- Added liquidity
- Innovation in computer technology
- Stabilization of market systems

Since HFT strategies require shorter evaluation period because of their statistical properties, they may not be suitable for long term portfolios. Many HFT strategies provide liquidity to the markets making markets smoother with less frictional costs in the heterogeneous market there may not be one best strategy that is fruitful all the time. It depends upon the stock selection, time and situation as well as the trading and risk profile of the investors.

Strategy	**Description**	**Typical Holding Period**
Automated Liquidity Provision	Quantitative algorithms for optimal pricing and execution of market making positions	< 1 minute
Market Microstructure Trading	Identifying trading party order flow through reverse engineering of observed quotes	< 10 minutes
Event Trading	Short-term trading on macro events	< 1 hour
Deviations arbitrage	Statistical arbitrage of deviations from equilibrium: triangle trades, basis trades, etc	< 1 day

Table 3: ***HFT Strategies (Source: Aldridge, 2009)***

Basically HFT strategies differ as per the holding period they use as well as the trading mechanism they use while trading the securities. Aldridge suggests these four different HFT strategies for high frequency traders. Aldridge (2009) includes three different HFT strategies as; Electronic market making, Statistical Arbitrage and Liquidity detection.

2.3.1 Liquidity provision or Market making strategy

Market making strategy is a mechanism of generating profit from bid and asks spread of the securities. This is also known as passive market making strategy. This strategy mimics the traditional role of market makers. After the immergence of HFT firms the liquidity of the market has increased along with decrease in bid-ask spread. To make money from the spread market makers quote offer price above the market price and bid price below the market price. In HFT the bid and ask quotes are generated automatically by using limit order via complex algorithms. Some HFT firms use pinging[10] to place limit orders so that they can quickly withdraw their orders before execution. Market makers are not obligatory to quote the market, so the lack of this formal obligation may reduce the liquidity when it is needed the most.

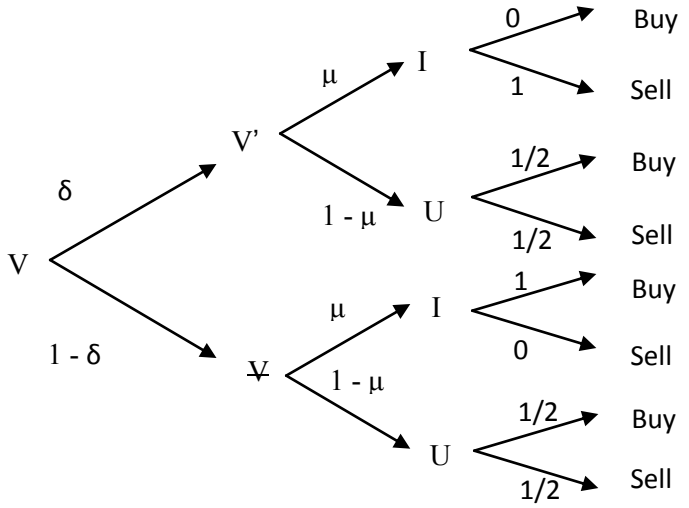

Figure 6: ***Basic sequential trade model (Source: Joel Hasbrouck, 2007, pg. 44-47)***

$$A = \mathrm{E}[\mathrm{V}|\mathrm{Buy}] = \frac{\mathrm{V}\,(1-\mu)\delta\ +\ \mathrm{V}'\,(1-\ \delta)(1+\ \mu)}{1-\ \mu(1-2\,\delta)}$$

$$B = \mathrm{E}[\mathrm{V}|\mathrm{Sell}] = \frac{\mathrm{V}\,(1+\mu)\delta\ +\ \mathrm{V}'\,(1-\mu\,)(1-\ \delta)}{1+\ \mu(1-2\,\delta)}$$

Bid-Ask spread is

$$\mathrm{A}-\mathrm{B} = \frac{4\,(1-\delta)\delta\mu\,(\,\mathrm{V}'\ -\mathrm{V})}{1-(1-2\,\delta)\text{^}2\ \mu\text{^}2}$$

In a symmetric case of δ = ½, A-B= $(\,\mathrm{V}'\ -\mathrm{V})\mu$

[10] pinging is a technique to enter into market through small marketable orders in order to learn about the large hidden orders hidden in exchanges.

The tightness of bid and ask spread can be measured continuously over the trading day using a simple method;

Tightness of Trading Spread= (Ask Price - Bid Price) / Bid Price

In this method an average time weighted spread is used to see the tightness of the spread. This technique would not be able to define the tightness of the spread if the two way quotes is missing. In tangible assets, market becomes tight when there is more demand than the supplies or the imbalance in-between demand and supply. Similarly, in intangible assets market, there are plenty of buyers and sellers in all the time which leads in the decrease in bid-ask spread. Market makers place limit orders on the buy side as well as sell side of the order book. They are responsible for providing liquidity for market orders. Market makers earn the spread between bid and ask by providing liquidity to the market. Market makers are also taking risk and there is the possibility that they will lose money with better informed counterparties. Market makers update their bid and ask price frequently based on the new market information, new order submissions and the cancellations.

HFT market makers are one of the counterparties of the normal market makers or the clearing members. They act little differently than the normal clearing members. They tend to place large numbers of add order to the limit order book and immediately cancel the same orders before executions of those orders. HFT market makers have replaced traditional market makers in recent dates. Traditionally market makers were used to be a human now market makers are more technologically advanced computers than humans. It is beyond the capability of humans to provide liquidity to high frequency traders manually. In most equity markets, liquidity providers also get liquidity rebates. Liquidity rebates is also known as market makers' fees.

There is another mechanism of providing liquidity which is also known as 'Make or Take' pricing. Where, this clearing member provides liquidity to outstanding limit orders placed by the customer, which is very lower or higher than the current market price. In return exchange rebates some portion of that access fee to the market makers as liquidity rebates. Market making strategy in HFT is challenging to get spread out of bid and ask as the spread might be lower than the transaction fees. Hagströmer and Norden (2012) show that NASDAQ OMX Sweden accounts around 72% of marketing making strategy among 86% of HFT Limit order data.

2.3.2 Market Microstructure trading

Market microstructure is the study of the process of exchanging assets under explicit trading rules. Market microstructure analyses about how some specific trading mechanisms affect the price formation process of a security. This price formation mechanism may include some intermediaries such as finance specialist, or exchange or some electronic interface. Market microstructure enhances the ability to show how different trading mechanism affects the trading protocol and price formation. How price exhibits certain time series properties. This helps in understanding the return generated by the financial assets as well as the efficiency of the market (Maureen O'Hara, 1995).

Joel Hasbrouck (*Empirical market microstructure: 2007,* pg. 7) provides the list of significant outstanding questions in market microstructure:

- What are the optimal trading strategies for typical trading problems?
- Exactly how is information impounded in prices?
- How do we enhance the information aggregation process?
- How do we avoid market failures?
- What sort of trading arrangements maximize efficiency?
- What is the trade-off between "fairness" and efficiency?
- How is the market structure related to the valuation of securities?
- What can market/trading data tell us about the informational environment of the firm?
- What can market/trading data tell us about long-term risk?

In this thesis we will answer some of the above questions. Market microstructure data are distinctive time series. In high frequency tick data generation, the millisecond time interval is not homogeneous. Tick price generation time interval from previous to the current and upcoming from current tick price is different. Highly liquid securities have less time interval in-between two tick price. Market microstructure shows the behavior of price and the market. Over the last decades, sophisticated automated technologies has created a new era in the world of electronic trading making micro-structure a very important tools to be understood in order to formulate HFT strategies. Price reversal strategy is one of the market micro structure strategies where the traders will try to reverse the price of the security by cancelling the large portion of his orders and by creating order imbalance.

Market structure has been changed in recent years creating more opportunities for AT and HFT. Traders can make profit from large buy and sell side orders. HFT can detect large pool of orders and they can anticipate the change and make profit accordingly. Sometimes large order detection is difficult if the trader is using some random strategies but for many HFT it is easier to achieve.

Lillo and Farmer (2004) show that when a trading firm is continuously placing large amount of orders that can create the imbalances that can be seen clearly as it tends to decrease the autocorrelations between the trade imbalances. Theoretically one can find the probability of imbalance direction using some forecasting tools, but in practical it is too complex. When there is diverse effect on the stock and its sector wise index that can be the indication of large orders by the HFT firms. This mispricing between the sector wise index and the particular stock of that sector can be the lead to the HFT and can get huge amount of profit. Some aggressive traders can easily anticipate the flow of large orders whereas passive investors can play the role of liquidity provider only. There is still some research gap to show that either HFT are engaged in order anticipation or not.

Baron et al (2012) empirically show that the profitability of aggressive HFT are usually higher than the inactive or passive HFT firms. Order anticipation can be done by the most active HFT firm who is getting news feeds microsecond sooner than other competing HFT firms, but it comes in a huge cost which is beyond imagination for normal HFT firms. To avoid the situation of easy anticipation HFT firms usually place their orders in small order sizes so that it will be difficult for other investor to anticipate the possible price change from the large order imbalances. It is even more difficult for market makers to minimize the impact created by the large flow of orders. When there is normal amount of trades flow with small trade volumes, it will be even more difficult for passive investors to anticipate the price change. Many HFT firms cancel their order before execution which makes market maker even more challenging but these days market making is also automated and it uses its own strategy for order detection. Since HFT firms are also acting as market makers it is rare to have order imbalance in the trading day. We can see some order imbalance in the opening and closing hours of the trading day but they are also there temporarily.

2.3.3 Event Trading

Sometimes market may take longer time to convey new information. There might be extremely active trading before and after the major announcement by the particular firm. The variation in the trading uncertainty is managed by the basic trading model at the starting of each business day and a random step can be added to capture the major event information (Easly and O'Hara, 1992).

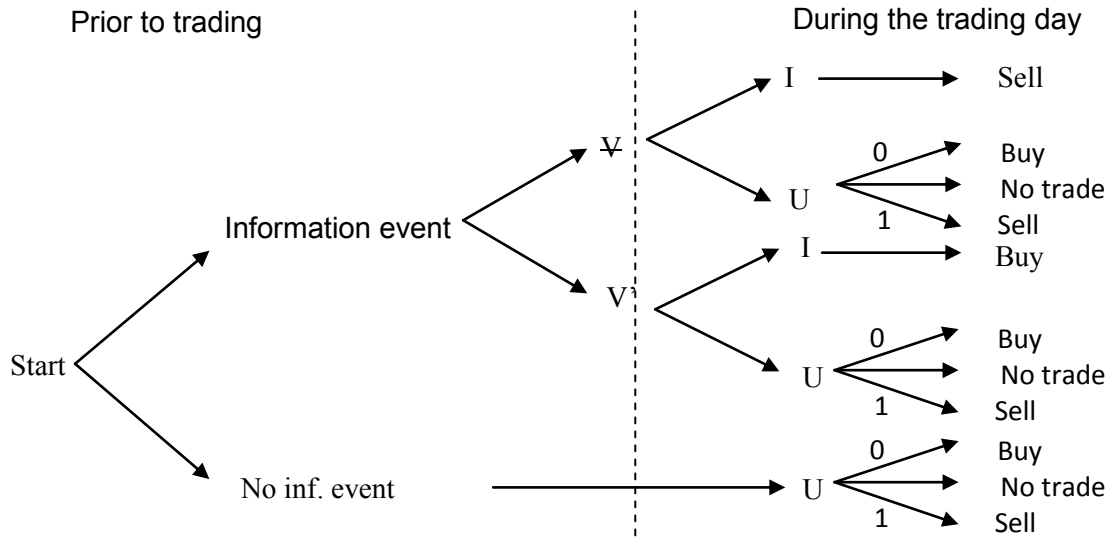

Figure 7: ***Event tree at the start of the trading day (Source: Easly & O' Hara, 1992, pg. 51)***

With fast and real time news reporting system, traders now can take the advantage in real time. Algorithms are written in such a way that it can differentiate the bad news from the good news. If the event is good (bad) for the stock, then the stock price of that particular firm will increase (decrease) so the algorithm trades accordingly. Easley et.al (1996) suggested a model to determine the probability of an informed trading of the particular asset. Where

α= information event that is observable to some of the traders

$1-\alpha$= probability of not having any information events

δ= probability of that information event which affects the value of the asset negatively

$1-\delta$= probability of that information event which affects the value of the asset positively

Both the informed and uninformed investors make trades and the arrival rate of the order is ε. The arrival rate also follows a process, μ. Uninformed traders makes random decision on trades on their own psychological and analytical basis whereas informed trades will place the orders according to the nature of the information. If they have positive information they will buy and, sell if they have negative information.

Easley et. al (1996) show that the probability that a trade that occurs at time *t* is informed is given by;

$$\mathrm{PI}(t) = \frac{(1 - Pn(t)))\mu}{(1 - Pn(t)))\mu + 2\varepsilon}$$

Where $P_n(t)$ is the probability of a "no event day" at time *t*.

Event trading is also known as directional trading or news based trading. Machines these days are programmed to read news. It analyses that good words and the bad words in the news and does the trading accordingly. Positive news with positive words like, increase, raise, promoted, higher can suggest the computer to buy the security for possible increment in the price of the security.

Many news agencies nowadays sell news to the HFT firms for sending them news prior to the release. This makes HFT firms aware of the possible event in advance which can be profitable, but relying too much on news agency might be harmful. Sometimes news is created by the news agencies it selves.

Hendershott and Riordan (2009) consider 25 largest HFT firms active in NASDAQ during the year 2008/9 and they found out that, each HFT firm earns average $2,351 per stock per day. They found that the statistical arbitrage works almost all the time, making 100% performance accuracy, whereas most of other HFT strategies works at least 51% of times.

News based trading uses textual information, its degree of importance, direction of the effect and potential outcome to do the trading. Information leakages from the employee to the HFT firms are threads to the exchange as they already know the and anticipate the effect of the news before it releases and they wait the right time of news flash and they initiate the trading capturing lots of profit.

2.3.4 Statistical Arbitrage

Statistical arbitrage strategy is the quantitative strategy and HFT applies these types of quantitative strategy in a fraction of second. Now it is possible because of sophisticated algorithms as it can sense the short-lived probabilities. Statistical arbitrage is one of the most used strategies from the HFT firms. In traditional way of trading, security mispricing used to be for longer time frame because of improper and slower communication channel. In today's modern society we have high speed internet and live news feed channel which makes mispricing a very short lived opportunity. There are various kinds of Statistical arbitrage strategies which can be used by non-HFT firms as well.

- **Market Neutral Arbitrage:** Market Neutral Arbitrage is taking long and short position of highly correlated securities. First buy and hold the instrument and start continuously shorting the correlated instruments. As they are correlated, the payoff of the positions offsets each other. To make profit out of this market neutral strategy, arbitrageurs sell the instrument that is making loss in its position and hold them which are making profit. When all the loss positions are settled and only wining positions are remaining in the trading platform, arbitrageurs start to settle the wining positions if the price is reversing. Market neutral strategy provides a safeguard from the price movements so it is highly attractive for HFTs and other traditional arbitrageurs. (Aldridge 2009).

- **Cross Assets, Cross Market and ETF Arbitrage Strategy:** This is a well-established statistical arbitrage strategy to trade securities and to get profit out of securities mispricing. When the same security has different prices in different market, arbitrager buys it in the lower price and sells it in higher price in different market where the same security's price is rated higher. There are so many platforms or the exchanges where the same security is listed. Having the higher number of market allowing the same security to trade generates higher amount of possibilities to have arbitrage opportunities. Not only the mispricing of the same security is only way of making money but also one can get profits from derivatives mispricing. Options are created from stocks as an underlying security, when the price of an option is fundamentally different from its market value then the arbitrageurs can make good amount of profit in short period of

time. Similarly exchange traded fund can be mispriced sometimes, as this kind of pricing inefficiencies last for short period of time, HFT firms use their speed to capture these kinds of opportunities. (Aldridge 2009). Essential factors in constructing Statistical Arbitrage strategy are *(Quant Congress USA, 2011)*;

- Proper and diversified selection of stocks/options/ETFs
- Captures the bid and ask spread
- Apply pairs trading according to the model
- Manage risk using real-time Value at Risk
- Execution using value weighted average price
- Avoid taking trading volume into consideration

Statistical arbitrage attempts to bet on the convergence and the divergence of price movements of pairs and baskets of assets, using statistical methods. The modern definition of statistical arbitrage is to spread the risk of a single trading among millions of other trading in a very short holding period, aiming for profit using the law of one price fundamentals.

A pair trading is one kind of market neutral statistical arbitrage strategy in HFT. Pairs trading can be based on two-stage approach, one is called correlation approach and the other is called co-integration approach. This type of statistical strategy is used to capture the statistical mispricing between pair based stocks.

These days, programmers, engineers and statisticians and many other interested are making complex algorithms for HFT to squeeze out every penny of returns possible. Many of the trading strategies are based on the intuition and the psychological state of mind of the trader rather than based on empirical analysis.

In statistical arbitrage using correlation for pairs trading is one of the tools. Price of the securities is correlated if they share same news.

- Positively Correlated: If same news is good for both and has positive price movements.
- Negatively Correlated: If same news is good for one and bad for another.
- Not Correlated: If one news is good or bad for one and neutral for another

Statistical arbitrage is a popular HFT strategies used by hedge funds and other trading houses. Statistical arbitrage uses cointigration to identify profitable trading opportunities. It attempts to get profit from the relative mispricing based on the historical price patterns. Arbitrage usually is riskless but statistical arbitrage is not riskless.

Ross (1976) Arbitrage Pricing Theory and the cointigration approach are related to each other. This strategy is also related to Law of one Price. If the two securities have similar cash flow trends then the price formation of those two stocks are expected to be similar.

2.4 Evaluating performance capacity of HFT strategies

2.4.1. Basic return characteristics

There are various kinds of trading strategies in high frequency finance and the most common motive of using these strategies is to generate profit applying them. Return can be measured in different time frequency like seconds, minutes, hours, days, years and longer. There are various performance measurement techniques to evaluate the basic return characteristics of these strategies. Most of the firm uses annual average return as a performance measure. All the trading firms prefer higher return. Average annual return, standard deviation, volatility and maximum drawdown, skewness, kurtosis are some characteristics for comparison between different strategies (Aldridge, 2009).

2.4.2. Comparative Ratios

Average return, standard deviation, skewness, kurtosis and other measure the basic return characteristics of the particular strategy. There are various comparative ratios which summarize the basic return characteristics. One of the most used ratios is Sharpe Ratio.

The comparative ratios used in this thesis are Sharpe, Omega, Sortino, Kappa, VAR and CVAR. Following are the comparative ratios suggested by Aldridge (2009)

- **Sharpe Ratio:** The Sharpe ratio is also known as return, per unit of risk often represented by variability, sometimes the unit of risk might be the standard deviation of the returns. Risk and return can be represented graphically. Generally return is dependent upon the level of risk taken, so return is shown in y-axis and risk is shown in x-axis.

  Risk averse investors always look for high return in low risk. Sharpe ratio measures the risk and return performance. Higher Sharpe ratio shows the better performance of the portfolio. Sharpe ratio measures the gradient of security market line from the risk free rate.

  Modigliani (1997) proposes an alternative risk adjusted return using Sharpe ratio, where the risk factor is the benchmark portfolio and allow direct comparison. Sharpe ratio helps in ranking the fund based on the order of preference. Ratios of the investment strategies can be grouped in two different categories such as; Sharpe type ratios where risk and return, risk adjusted return suggested by

Modigliani (1997) and the next category is descriptive statistics, where the ratio only can provide the pattern of the return but cannot suggest either the return is good or bad. The only thing is, investor prefers lower volatility, lower variance but the higher average return. Many investors also look at the tail of the return distribution. They prefer positive skewness along with lower kurtosis. Pezier (2006), suggest an adjusted Sharpe ratio which rewards positively skewed and lower kurtosis and thus able to satisfy the criticism of Sharpe ratio.

- **Treynor Ratio:** Treynor ratio is similar to Sharpe ratio but the measure of risk in Treynor is the systematic risk only. In Sharpe ratio, total risk is used as a risk measure to calculate the reward to risk ratio. Many portfolio managers avoid using Treynor ratio because it ignores the specific risk factors. Treynor Ratio is developed by Jack Treynor. It measures the excess return over market return which could have been earned on a riskless investment per each unit of market risk.

- **Jensen's Alpha:** Jensen's alpha is another useful performance analytics; it shows the excess return adjusted for systematic risk. Many times Jensen's alpha is used wrongly as the investment manager's performance over benchmark portfolio. It is a risk-adjusted performance measure that calculated the average return on a portfolio over the predicted return by the Capital Assets Pricing Model.

- **Omega:** Shadwick and Keating (2002), suggest a ratio called Omega that gives the information in the higher moments of a return distribution. Omega is also known as gain-loss ratio which implicitly adjusts both skewness and kurtosis, considering upside and downside potential.

- **Sortino Ratio:** Sortino (1991) suggests an extension of Sharpe and Omega called Sortino ratio which uses downside risk as the risk factor in the denominator. Since upside return movement is good for the investors, it only takes downside return movement as risk factors. So, in Sortino ratio, the total risk is simply replaced by the downside risk.

- **Calmar Ratio:** The Calmar ratio is a Sharpe type measure, which uses the maximum drawdown rather than total risk. If lower the Calmar Ratio, the worse

the strategy performance on a risk adjusted basis, similarly higher Calmar ratio suggests better strategy performance. It is developed by Terry W. Young (1991). Calmar ratio is typically based on recent and short-term data.

- **Appraisal ratio:** Treynor and Black (1973) suggest appraisal ratio which uses Jensen's alpha. They use systematic risk adjusted excess return divided by the specific risk factors which measures the systematic risk adjusted return for each unit of specific risk taken.

- **Sterling Ratio:** The Sterling ratio replaces the maximum drawdown in the Calmar ratio with average of largest drawdowns. This ratio is mainly used by the hedge fund managers. It determines which hedge funds have the highest returns with less volatility. Similar to Calmar ratio, higher sterling ratio is better which means that investment strategies are making higher return relative to risk.

- **VaR (Value at Risk):** VAR is a statistical technique which measures and quantifies the level of financial risk. Many investment managers use VAR to measure and control the level of risk that firms undertake. The job of the investment manager is to ensure that risk taken by his firm is not beyond the level which firm cannot absorb the losses of a probable worst case scenario. Value at Risk measures three things, the potential loss amount, probability of that loss to be occurred, and the investment time frame. All these ratios are very familiar for portfolio managers. Recently hedge funds are using more risk associated with different types of investors. Value at Risk (VaR), is also a Sharpe type measure where total risk is replaced by the VaR.

- **CVaR (Conditional Value at Risk):** Conditional value at risk is also called expected shortfall. As similar to Conditional Sharpe, in Conditional VaR, conditional variance is replaced by conditional value at risk. VaR is unable to provide the information about the size and shape of the tail, thus it is not so good measure of risk for many investors. Conditional VAR overcomes this drawbacks and it can give the expected shortfall, expected mean loss and the shape of the tail.

2.4.3. Performance Attribution

Attribution analysis aims to differentiate between selection strategy and market timing strategy on the superior performance of the portfolio. This analysis compares the actual return of the investment manager with the predefined benchmark. Attribution analysis subdivides the actual return into selection effect and allocation effect. Performance attribution is also known as investment performance attribution. It is used to describe why some portfolios outperform the benchmark. Investor with active trading strategies can outperform the benchmark where as for the passive investor it is hard to outperform the benchmark. There are various kinds of attribution analysis for various kinds of portfolios. Active portfolios and passive portfolios use different methods in explaining the performance attribution. Attribution is also known as benchmarking. Various scholars like, Ross (1977), Sharpe (1992), Fung and Hsieh (1997) applied performance attribution analysis to trading strategy. Doing regression of various factors into one basket of the factors with strategy's return is a way to get performance attribution of that particular portfolio, Aldridge (2009).

$$\mathrm{Rit} = \alpha\mathrm{i} + \sum_{k} b\mathrm{ik}F\mathrm{kt} + \mu\mathrm{it}$$

Where,

- b_{k} measures the performance of factor k.
- α_{i} measures the persistent ability generating abnormal returns, and
- μ_{it} measures the idiosyncratic return of the strategy in time period *t*.

Fung and Hsieh (1997) use eight global groups of asset classes to set as a performance attribution benchmark. Performance attribution is a good measure of return generated by applying the strategy. It shows the investment styles and the design of the investment strategy. It gives grounds for comparison between different other strategies. Performance attribution helps in forecasting strategy performance (Jagadeesh and Titman, 1993).

2.4.4. Other Forms of Strategy Evaluation

Strategies are time dependent. Same strategy may not be profitable in all kind of situations. Though there are so many other strategies with different names, the main goal of them is to make profit. Some makes profit from the bid ask spread using

market making strategy, some uses quantitative strategies like statistical arbitrage to make profit. Buying in lower price and selling in higher price is not the only way to make profit these days. Capacity of each strategy is measured based on their performance over benchmarking. Other form of strategy evaluation includes;

- **Strategy Capacity:** Strategy selection can be based on the amount of investment and the liquidity of that instrument. Placing large amount of orders is also not considered good if there is liquidity problem. In HFT strategies are used to capture the ounce from every trade which is not seen significant if treated as a single trade but when multiply it with the huge amount of trade volumes then every second there is high amount of profit generation.

- **Length of the Evaluation Period:** There is always a question about selecting the best evaluation period. Long term investors basically like to consider longer time period into consideration while short term investors see the price movements in the short period of time. Long evaluation periods generally means the period between six months to two years where short period is considered to be an intraday period up to one month. The higher the value of Sharpe ratio, the shorter must be the evaluation period to assure the validity of Sharpe ratio (Aldridge, 2009).

- **Autoregression-Based Test:** If the market is efficient it is harder for the investment managers to make strategies which lead them to huge amount of profits. Trading strategies work better in the least efficient market. In perfect efficient market, prices reflect all the current available information, thus suggesting no dependencies from past price movements. Explanatory power of past price is one way to measure market efficiency. Mech (1993) and Hou & Maskowitz (2005) give one effective measure to find the market efficiency by finding the difference between Adjusted R-Squared coefficients of restricted and unrestricted model. The main difference between restricted and unrestricted model is that, restricted model restricts all coefficients of beta to be zero. Inefficiency close to zero shows market is efficient and close to one shows market is inefficient.

  Market Inefficiency= 1- [R^2 (Restricted) / R^2 (Unrestricted)]

2.5 Literature Review

Many HFT strategies use the speed advantage as they can process information, make orders in a very short period of time in very large scale. Cartea et al (2011) have distinguished two types of market orders as influential and non-influential. If any orders affect the shape and dynamics of LOB then the orders are influential where as if the orders have no any effect in LOB then they are non-influential. This thesis will look for the influence of HFT activities in LOB after excluding non-HFT activities. Kumar et al (2011) show that, US has over 70% HFT activities in equity market and European equity market has around 40% HFT activities. Asia is also in increasing phase and it has around 10% of HFT activities. The increasing popularity of HFT in Asia in recent days can make the Asian stock market more active and volatile. In this thesis, the influence of HFT in Finnish stock market will be studied. Cartea et al (2011) have another contribution in optimal high frequency trading strategy. They model short-term alpha in the drift of the mid-price as a zero-mean reverting process. The drift fluctuates randomly when there are influential orders in the order book or some event driven trading. Since the same stock can be traded globally, any incident in one part of the globe can create chaos in another part of the world. Event is an important hint for HFT traders. They always seek for some major events which are not yet confronted towards the public by any public channels or media. Market event has an important impact in the arrival of influential orders. Market news can be good, bad or ambiguous. As per the nature of the news order submission on buy or sell side is determined by the traders. Good news generally increases the value of the firm so traders prefer to buy and sell if the news is bad. If the event is ambiguous then traders can apply market neutral strategy.

(Almgren and Chriss, 2000) is one of the most widely used models for execution strategy. A key input for execution strategy is the length of execution horizon. This is typically set as exogenous, with an estimate. The execution horizon may differ as per the strategy used but sometimes HFT firms uses the same order duration and holding period horizon. Using dynamic strategies will differentiate between the gains and losses and lengthen its horizon to capture the profit. Kearns et al (2010) empirically show that profit generated by most of the HFT firms is centered to few highly liquid stocks. Individual investor can wait for their price level but it is difficult to complete trades in certain price time priority. To overcome this kind of situations HFT firms

use highly aggressive strategies with some cost. HFT in such securities can be profitable using aggressive trading styles. There is chances of high bid and ask spread as well. If there is large amount of market orders in the queue then those orders can be absorbed in the same price level. Pragma (2012) shows that HFT firms are concerned in the most liquid stocks only, as they can take the advantage of high speed price change or the tick price. We will check the concern of HFT firms on Finnish stock market. Highly liquid stocks sometimes experience crowding from the market maker and it is difficult to determine the best bid/ask price. Easley et al (2011) state that speed is not always the advantage for HFT firms, since they use volume time instead of chronological time. Skouras and Farmer (2013) say that besides any effective HFT strategies, HFT firms use their speed advantages to be ahead of the queue among other market participants and manipulate the market. Leinweber (2009), Technological advancement is not only making it easy for HFT firms to get profit by employing their strategies and speed but also it is making them difficult as their counter parties are also using the same level of technology.HFT firms use the benefit of speed so that they can place and withdraw their position from the limit order book. If they are not been able to cancel their position in current market price that will create market liquidity risk. Bervas (2006) states three different criteria to measure the liquidity and they are;

- Tightness of bid-ask spread: Bid-ask spread identifies the cost of immediate reversal of the position
- Market depth: It is the volume of that particular security which can be bought or sold in the same best selected price without price slippage.
- Market resilience: It measures the speed of price reversal to equilibrium price after a significant increase in order flow.

The optimal HFT strategy shows how to optimally submit orders, optimally determine the cancellation and execution rate based on the news or the market events. Optimal HFT strategy helps in identifying HFTs from AT based on the characteristics of the trades. Cartea et al (2011) test their model using simulations where they take that information which can be processed and incorporated in sending optimal trading orders. Many HFT orders are withdrawn from the market as the limit orders are driven by the better informed traders. They also show that those who are unable to make profitable strategies can systematically stay in business if they have enough controls over their inventories. Cartea and Penalva (2010) suggest “spoofing”

where the traders send a large pool of orders in either side of the limit order book and after triggering the opposite side of the order book they immediately cancel the orders and place the orders in other side of the limit order book. Aldridge (2009) says that, HFTs mostly follow the highly liquid stocks; this is because of tick data generation time interval. Highly liquid stocks generates tick price regularly in a very short time interval. This will help high frequency traders to trade in time volume. Heston et al (2010) show that though different HFT firms use different HFT strategies but institutional HFT investors leave a noticeable pattern in their trading activities which makes it easier to copy the HFT strategies. Barber et al (2009) state that, retail HFT are usually the noise traders and they trades in a very small fragments and so it is difficult to detect the trading pattern of retail HFT traders. We will check the higher order fragmentation on all the selected stocks. Hagströmer & Norden (2013) emphasizes how different HFT strategies influences on market quality. They focus particularly on market making strategy on NASDAQ OMX Stockholm market. This thesis will check market marking and other strategies on NASDAQ OMX Helsinki. Gencay (1998) states that, the ultimate goal of any HFT strategy is to generate profit. Sandro et al (2008) study the trading imbalances and the predictable price reversals. They find that imbalances generate predictable reversal in stock return. Any imbalances in one security affect the trade balance of another stock as well. The net order imbalance is seen only at the very beginning and very ending of the trading day. These types of orders imbalance do not necessarily create price reversal. It might affect the opening price of next day's. Chordia et al (2000) find the impact of order imbalance in liquidity and market returns. They studied with the data from New York Stock Exchange. They show how order imbalances in any direction either buy or sell reduces the liquidity of the market. Traders may be able to control the volume and liquidity but market return is always affected by the net order imbalance, suggesting market micro structure strategy as a tool to generate profit. Reberto et al (2002) empirically show that, not only price and return are random but also the waiting time between the two transactions also varies using high frequency data. Generally the waiting time in HFT is determined by the possibility of converting the position into profit. Waiting time varies from one position to another and from one stock to another based on the market movements as well as the possibility of positive return. We will check the order duration to compare the average waiting time of all the selected stocks.

3. DATA AND RESEARCH METHODS

This section includes the availability and description of high frequency limit order data used in this thesis. It provides a clear picture about the structure of high frequency data sets in a millisecond time interval. The raw data generated by the file delivery system of NASDAQ OMX includes all of the trading activities. It is in the hand of the author to consider the required message feed for the primary data sets for further empirical analysis. Basic limit order book activities are studied for the selected stocks which includes add, cancel and execution actions. The order generating pattern and the order imbalance is also studied for each selected stock. Empirical research methodology in this thesis follows multiple steps to come into conclusion. First a return series is generated following the respective strategy with the respective holding period as suggested by Aldridge (2009). Comparative ratios are calculated based on the return series. Then, this thesis uses the OLS (Ordinary Least Square) estimation method by using ARMA (Autoregressive Moving Average) model for the respective return series. Next, for the autoregressive based test for market inefficiency we identify the restricted and unrestricted R-squared required to calculate the market inefficiency. Conclusion is drawn based on the significant excess return, comparative ratios and inefficiency of the return series for each respective strategy's holdings for both long and short positions.

3.1. Data Availability

The data used in this thesis is one month high frequency limit order and tick data from NASDAQ OMX Nordic. The data is generated by Helsinki Stock Exchange Automated Trading and Information System for the month of November 2013. By paying the subscription fee to the exchange, data can be downloaded whenever needed taking into consideration some limitations. File Delivery System (FDS) of NASDAQ OMX provides the basic data which includes the limit order data. The ITCH data includes all the order book activities of stocks listed in NASDAQ OMX Nordic (Helsinki, Stockholm and Copenhagen) exchanges. Since the motive of this thesis is to study the performance capacity of HFT strategies in the context of Finnish stock market, we take into consideration the Helsinki exchange only. There are more than 136 Finnish stocks listed in NASDAQ OMX Helsinki. For the study of

performance capacity of high frequency trading strategies applied in trading stocks, this thesis selects six highly traded stocks based on the activities in the limit order book for the month of November 2013 and the highly traded stocks are; Nokia, Stora Enso, Nordea, Metso, Outokumpu and Nokian Renkaat.

3.2 Data Structure

NASDAQ OMX Nordic offers data feed in ITCH protocol. ITCH is direct data-feed such as TCP (Transmission Control Protocol) or UDP (User Datagram Protocol). In ITCH traders track the status of each order from order generation to its execution or cancellation. ITCH is mainly for information exchange only. Each information message length is based on its type. Subscribers can also get administrative messages if they have proper subscriptions. Messages send using ITCH, use high level of protocol so that the message is properly sequenced and guaranteed delivery. There are three different ITCH protocol options used by NASDAQ OMX Nordic and they are;

- **SoupTCP:** This protocol uses the single outbound channel for all securities using transmission control protocol.

- **Compressed via SoupTCP:** This protocol also uses the single outbound channel for all securities via transmission control protocol, but the protocol option can be offered to the members of exchange.

- **MoldUDP:** This also uses the single outbound channel for all securities via user datagram protocol.

ITCH is a direct data feed offered by the NASDAQ OMX Nordic with the following data structure and elements.

- **Order Level Message:** ITCH uses a series of order messages from the beginning of order generation to the end till its execution or cancellation. Exchange will provide its full order description using the standard ITCH protocol.

- **Trade Message:** ITCH provides separate message to reflect cross transactions. ITCH supports message that can reflect non-displayable order in the system to ensure customers have complete information about the trade flow.

- **Net Order Imbalance Message:** To calculate the best opening and closing price of the stock at the very beginning and closing of the trading day, the system calculates the equilibrium price along with the imbalance direction and quantity. The equilibrium price calculation includes both the displayable and non-displayable order types. Net order imbalance is helpful in predicting the best opening and closing price of the security to the public.

- **Administrative message:** Administrative message includes the trading actions and symbol directory message. Trading action message informs traders either the security is available for trading or not, it also shows if the security is halted or released for trading. Symbol directory message includes all the basic information about the security such as financial status.

- **Event Control Message:** This message type includes the trade events such as the opening of trading day, end of the trading day as well as the states of the different market segments.

NASDAQ OMX Nordic use separate time stamp message for efficiency reason to its ITCH product. ITCH provides sequential data feed so that the subscriber can get the trade message in proper time stamp. Time stamp in ITCH is separated first as second message and within each second message millisecond message is generated which includes all the trading action and order level data. For each second nine hundred ninety-nine milliseconds are generated, when the millisecond touches one thousand it jumps to next second and the same process continues.

For more information on the File Delivery System (FDS) of NASDAQ OMX Nordic, see this link: http://www.nasdaqomx.com/digitalAssets/89/89849_fds_-guideline_20130117.pdf

3.3 Data Description

Data received from the NASDAQ OMX Nordic from one month subscription includes the high frequency order level activities generated in ITCH system. The ITCH message includes the following information need for this thesis;

ISIN: International Securities Identification Number

OrderRefNo: Order Reference Number to identify each unique order placed in increasing pattern.

BuySell: Indicates either the investor is long or short by indication "B" for buy and "S" for sale.

Millis: Millisecond time stamp in increasing number. 1000 Milliseconds = 1 Second.

Action: It indicates the particular action in limit order book by the investor. It includes four different actions and they are;

- "**A**" = Order is added in limit order book
- "**X**"= Order is cancelled from the limit order book
- "**D**"= Order is deleted from the limit order book
- "**E**"= Order is executed

Quantity: It shows the number of buy or sells order added / cancelled / deleted / executed from the limit order book.

Date: It shows the particular day of limit order book activities in yyyymmdd format.

ISIN	OrderRefNo	Buy/Sell	L.Price	Millis	Action	Qnty	Date
FI0009000681	5242079	S	5.63	45138586	A	4557	20131101
FI0009000681	5242079	S	5.63	45138819	X	957	20131101
FI0009000681	5242079	S	5.63	45138819	X	3000	20131101
FI0009000681	5242079	S	5.63	45144398	D		20131101
FI0009000681	5242080	B	5.615	45138586	A	4000	20131101
FI0009000681	5242080	B	5.615	45138602	X	3000	20131101
FI0009000681	5242080	B	5.615	45138602	E	1000	20131101

Table 4: ***Nokia LOB sample***

Note: Data presentation format is solely in the hand of the author of this thesis. The data feed generated from ITCH protocol can be read using some programming languages and statistical software.

4. EMPIRICAL ANALYSIS

In this section we do the statistical analysis of the available data with the pre-specified methodologies. The empirical analysis part of the thesis mainly focuses on the three empirical activities of the top six mostly traded Finnish equities listed in NASDAQ OMX Nordic. At first, the basic limit order book activities of all the selected stocks including and excluding non-HFT activities will be analyzed. It is to make sure that all the selected stocks have the influence of HFT traders, so that the obtained result will be more accurate. The next step in the analysis is to apply the HFT strategies and the respective holding periods of the strategies to generate the return series. The return series then follow the ordinary least square method of estimation using the ARMA model to find out the intercept. The significance of the strategy is measured from the statistically significant intercept. Different comparative ratios are calculated for the comparison between the strategies of HFT and non-HFT traders holding long and short positions. The final step in the analysis cross checks the inefficiency in the market via autoregressive test.

4.1. Limit Order Book (LOB) Activities

NASDAQ defines Limit Order Book (LOB) as a record of unexecuted limit orders maintained by the specialist. These orders are treated equally with other orders in terms of priority of execution (www.nasdaq.com).

Rank	ISIN	Stock	HFT Activities of that month	HFT Activities 1st Nov 2013
1	FI0009000681	Nokia	3981326	254130
3	FI0009902530	Nordea Bank	3061289	137108
2	FI0009005961	Stora Enso	2738642	141569
4	FI0009007835	Metso	986465	73641
5	FI0009005318	Nokian	917992	67806
6	FI0009002422	Outokumpu	420762	66452

Table 5: ***Number of activities in LOB as on November 2013***

Note: HFT activities from the limit order book is counted based on the duration of order. If the particular order is stayed overnight then it is not considered as high frequency order. Order reference numbers which are not repeated on the same trading days are excluded from the HFT order book.

Nokia is the most highly traded Finnish stock listed in NASDAQ OMX Nordic with highest HFT activities. Nordea share is also traded in the similar manner to Nokia. The number of high frequency trading activities is decreasing rapidly in each successive stock. Top three has significant numbers of HFT activities where are other three has less impact by the HFT traders. But the HFT message generated is clearly visible in all six stocks.

Stocks	Order Duration		Order Duration		Max. Price		Min Price		Std. Dev	
	Max	Min	Mean	Median	Bid	Ask	Bid	Ask	Bid	Ask
Nokia	36874.92	0	778.2073	3.368	6.03	6.8	5.11	5.535	0.1161	0.1176
Stora Enso	35524.11	0	552.1229	2.789	7.535	8.02	6.465	6.825	0.1519	0.1493
Nordea	36127.53	0	443.9333	1.969	9.545	10.32	8.235	8.93	0.1616	0.1560
Metso	36890.21	0	696.2625	2.853	30.45	32.14	26.88	28.46	0.3849	0.3862
Nokian	30349.5	0	556.6366	2.086	38.72	41.25	34.31	36.08	0.4797	0.4859
Outokumpu	36892.32	0	868.0858	39.552	4.99	4.5	3.596	3.751	0.0132	0.0123

Table 6: ***The most traded Finnish stocks with limit order duration and Limit Order Bid-Ask statistics***

Median shows the order duration in limit order book before the order either cancelled or executed. The lowest duration is for Nordea, which is just 1.69 second. The average order duration of top five highly traded Finnish stocks is around 2.61 seconds whereas the average of top six is 8.77 seconds. The maximum order duration of all top six is less than few hours before the trading day. It shows that high frequency traders do not carry their positions till the last hour of the trading day. There is a risk of trading imbalance at the very beginning as well as at the very ending of the trading day. It is because of the carry forward positions of the non-high frequency traders.

The order duration of Outokumpu also suggests that there is less influence of HFT traders. Order duration in LOB for other stocks is less than 3 seconds whereas the Order duration of Outokumpu is around 40 seconds. The deviations in bid and ask tick price generation is higher for Metso and Nokian allowing the short term volatility traders to capture the profit. The bid ask tick fluctuations is lowest for Nokia as it is the most liquid among top five. Since the share price of Outokumpu is the lowest the tick price fluctuation is also lowest in it. HFT activities in Nokia is highest because of lower share price as same level of balance can be used to acquire more number of shares in comparison to other four stocks except Outokumpu.

4.2. Basic LOB activities of the selected stocks

- **Nokia:** Nokia is a mobile technology, network infrastructure, location services and other technology providers worldwide. It has headquarter based in Espoo, Finland. It is still one of the major providers of mobile technologies and devices. Nokia is now owned by Microsoft as it signed an agreement in September 2013 to sell its devices and services (www.nokia.com).

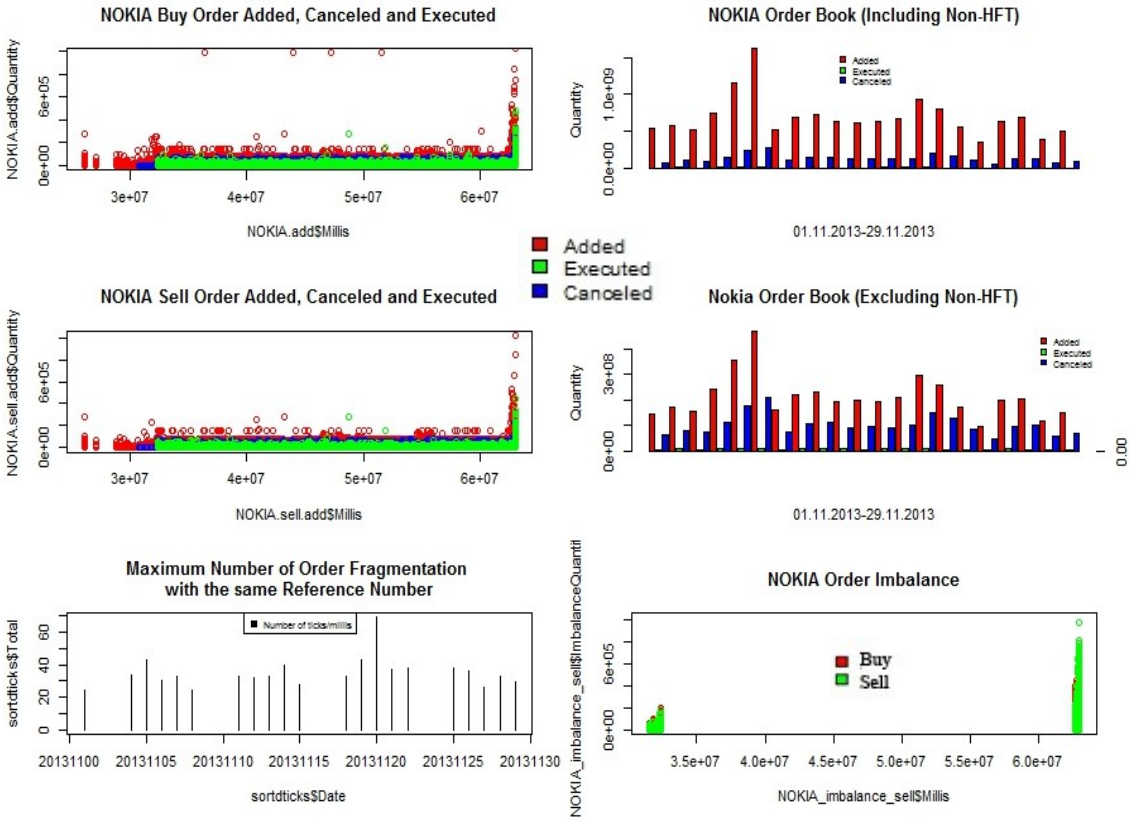

Figure 6: ***Basic LOB activities of NOKIA for the month of Nov 2013***

Based on the LOB activities, Nokia is the highly traded stock among other Finnish stocks in NASDAQ OMX Helsinki. The effect of HFT can be clearly seen in the above graph where most of the orders are cancelled before execution. Nokia seems to be favorite not only among HFT traders but also among retail investors. After removing non-HFT activities from the LOB, the cancellation ratio has increased significantly to more than 50%. The average order duration after removing the non-HFT activities of Nokia is 3.37 seconds. There is huge order imbalance at the very beginning and ending of each trading day. Sell side order imbalance is significantly higher than the buy side imbalance and the imbalance is higher at the end of the trading day. The graph shows plenty of carry forward positions. It suggests that some HFT firms left overnight positions as well. *(See Appendix 1 for highest order fragmentation pattern of Nokia from a particular investor).*

- **Nordea:** Nordea is a financial services group in the Nordic and Baltic region. Nordea offers online banking and insurance as well as information to investors (www.nordea.com).

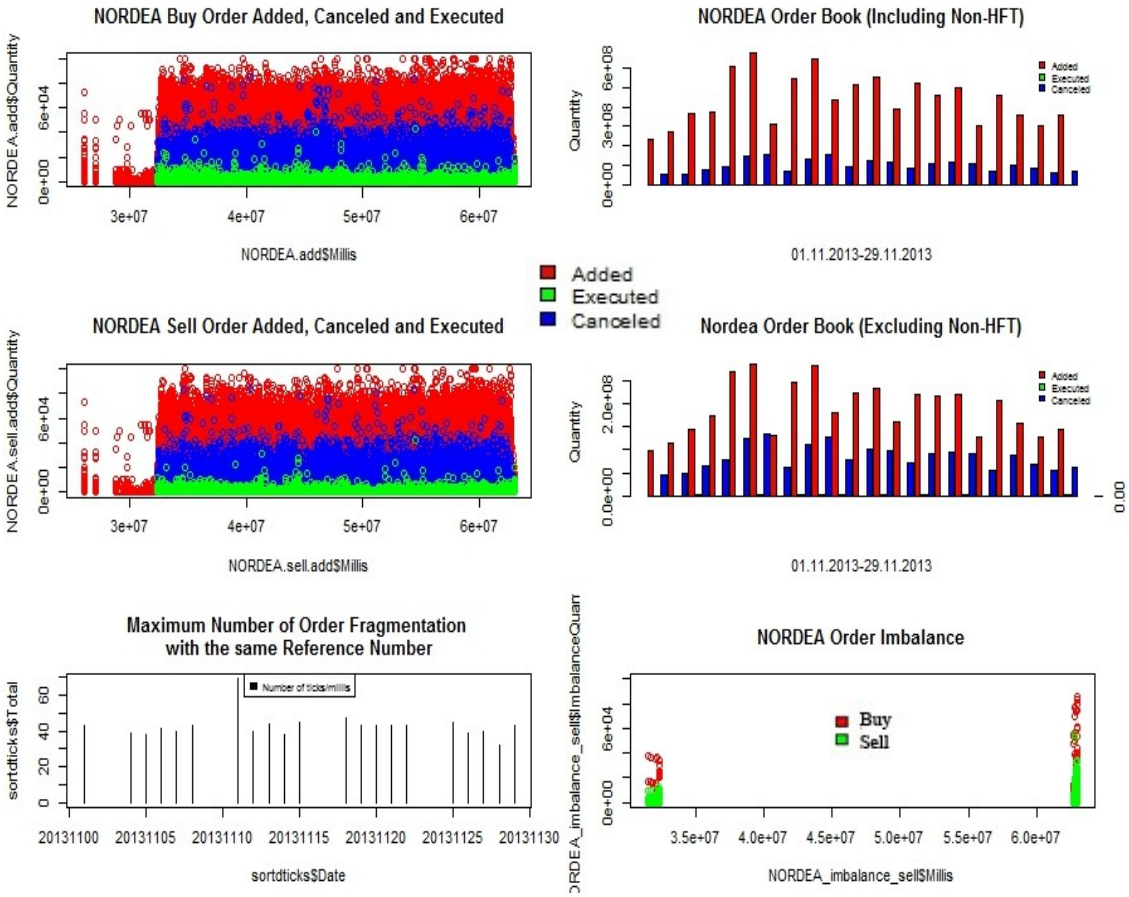

Figure 7: ***Basic LOB activities of NORDEA for the month of Nov 2013***

Nordea comes in second place of hghly traded stocks in Finnish stock market based on the LOB activities. We can see the similar pattern of order cancellation in both the buy orders and sell orders added to LOB. The order cancellation is around 50% where around 20% of orders seems to be executed.

After removing the non-HFT activities from LOB the execution rate seems to be less than 10% of overall added order. Here the order imbalance of Nordea is more on the buy side. Order imbalance at the beginning of the trading day is comperatively larger than the imbalnce at the end of the trading day. The average order duration of Nordea in HFT LOB is 1.97 seconds. Based on the quick liquidity Nordea comes in the first place of highly liquid stock in Finnish stock market. The order fragmentation pattern of Nordea is almost similar to Nokia. *(See Appendix 1 for highest order fragmentation pattern of Nordea from a particular investor).*

- **Stora Enso:** Stora Enso is one of the biggest manufacturers of wood products, papers, packaging and biomaterials. It has its operation worldwide with more than 29000 employees. Stora Enso is a publicly traded company listed in NSADAQ OMX Helsinki and Stockholm (www.storaenso.com).

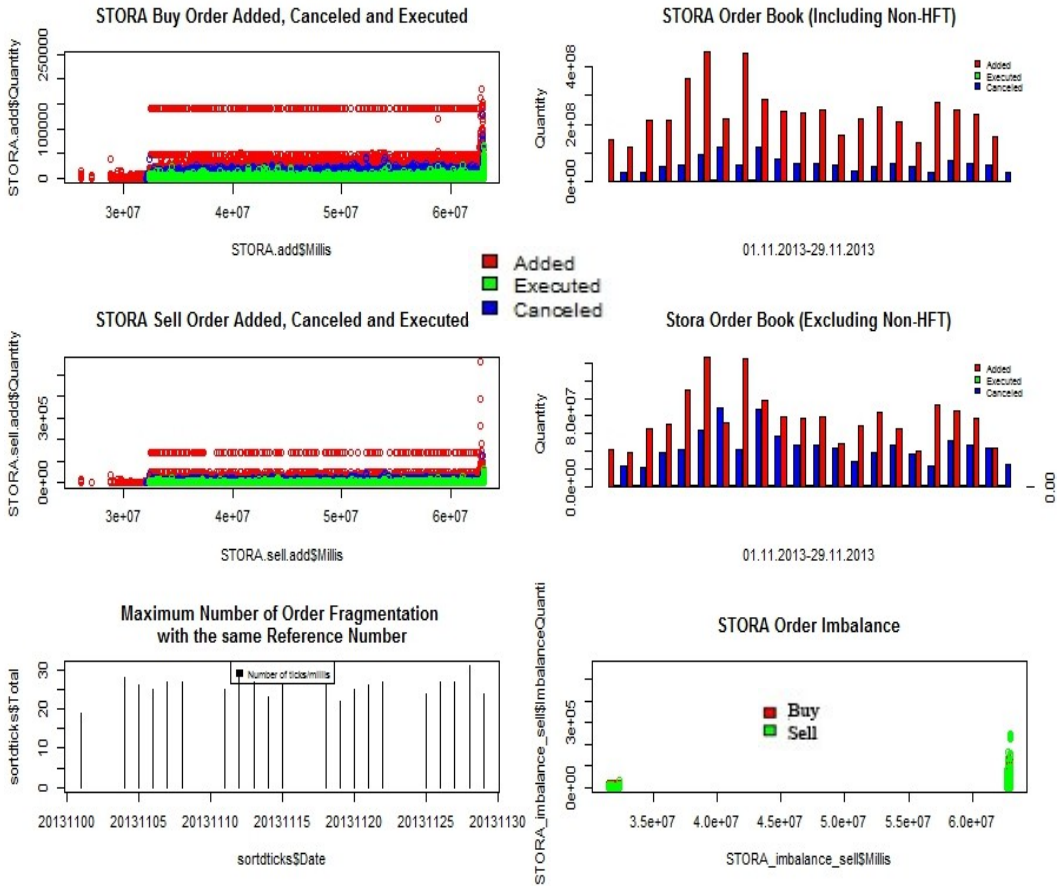

Figure 8: ***Basic LOB activities of STORA ENSO for the month of Nov 2013***

Stora Enso is also one of the highly traded stock in Finnish stock market. A clear impact of contineous HFT activities can be seen in both the added buy and sell order. More than 100,000 number of shares have been added in LOB for the whole month and the cancellation percentage is just slightly above the execution percentage. After removing the non-HFT activities form the LOB the cancellation percentage seems to be more than 60% of the added order. The average order duration of Stora in HFT LOB is around 2.79 seconds. The order imbalance of Metso is not so huge at the beginning of the trading day. The sell side order imbalance seems little bit higher at the end of the trading day but the buy side imabalnce is not so noticebale. Order fragmentation seems similar for most of the days. *(See Appendix 1 for highest order fragmentation pattern of Stora Enso from a particular investor).*

- **Metso:** Metso focus on smart solutions, mining, construction, and oil and gas industry. It also continues the process of automation solutions and flow control solutions and services for the pulp, paper and other areas (www.metso.com).

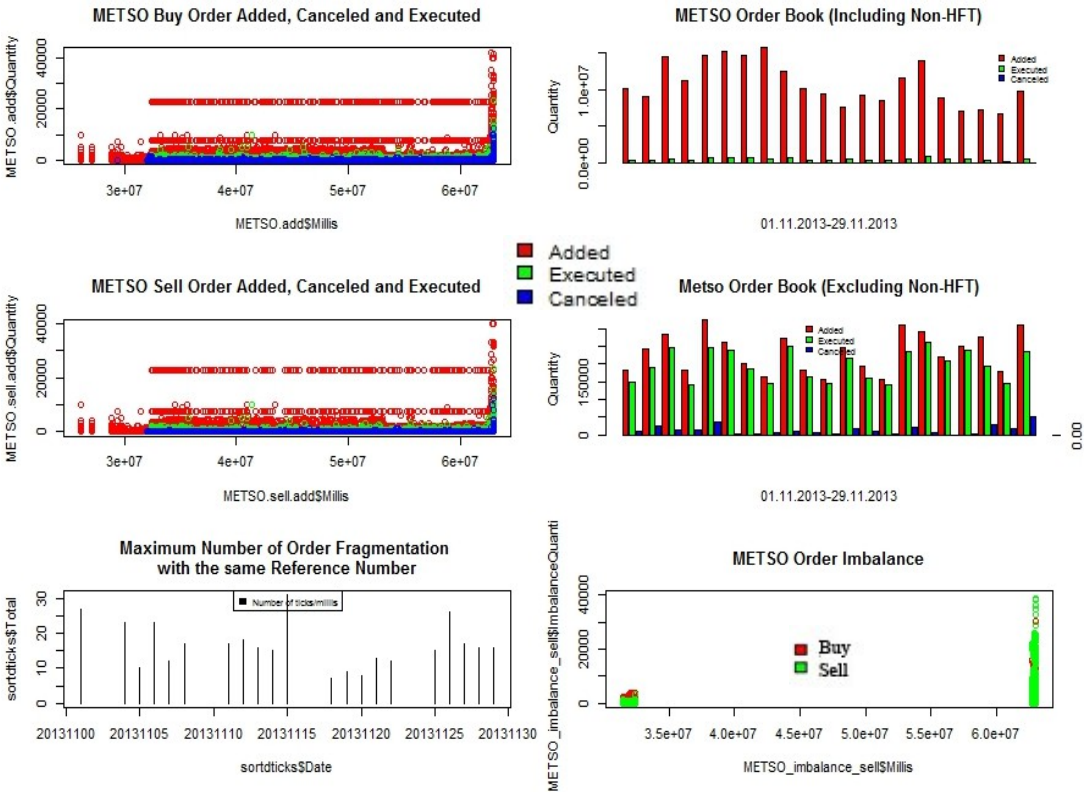

Figure 9: ***Basic LOB activities of METSO for the month of Nov 2013***

Metso is the most preferrable stocks among both the HFT and non-HFT traders. As similar to Stora, a clear pattern of adding buy and sell orders in LOB can be seen in the above graph. More than 20,000 numbers of shares are added in LOB before cancellation or execution. Here cancellation rate is lower than the execution rate even before removing the non-HFT activities. Green bars in the above graphs shows the number of executed shares. Before removing the non-HFT activities the execution and cancellation are rarely vissible in the graph, but after removing the non-HFT activities the Metso Order Book (Excluding Non-HFT) shows that the execution rate is more than 90% for Metso. HFT traders are acting like retail investors incase of Metso as they are executing most of their added orders. The average order duration of Metso in HFT LOB is around 2.85 seconds, which is slightly higher than of Stora. Sell side order imbalance of Metso is quite high at the end of the trading day. Order fregmentation pattern is different for most of the days. *(See Appendix 1 for highest order fragmentation pattern of Stora Enso from a particular investor).*

- **Nokian Tyres (Nokian Renkaat):** Nokian Renkaat is the automobile tire manufacturer that provides safe transportation facilities in Nordic conditions. It makes all types of tires for cars, trucks and other heavy vehicles suitable for any weather conditions. Winter tires in Nordic countries are only manufactured by Nokian Rentaak (www.nokianrenkaat.fi).

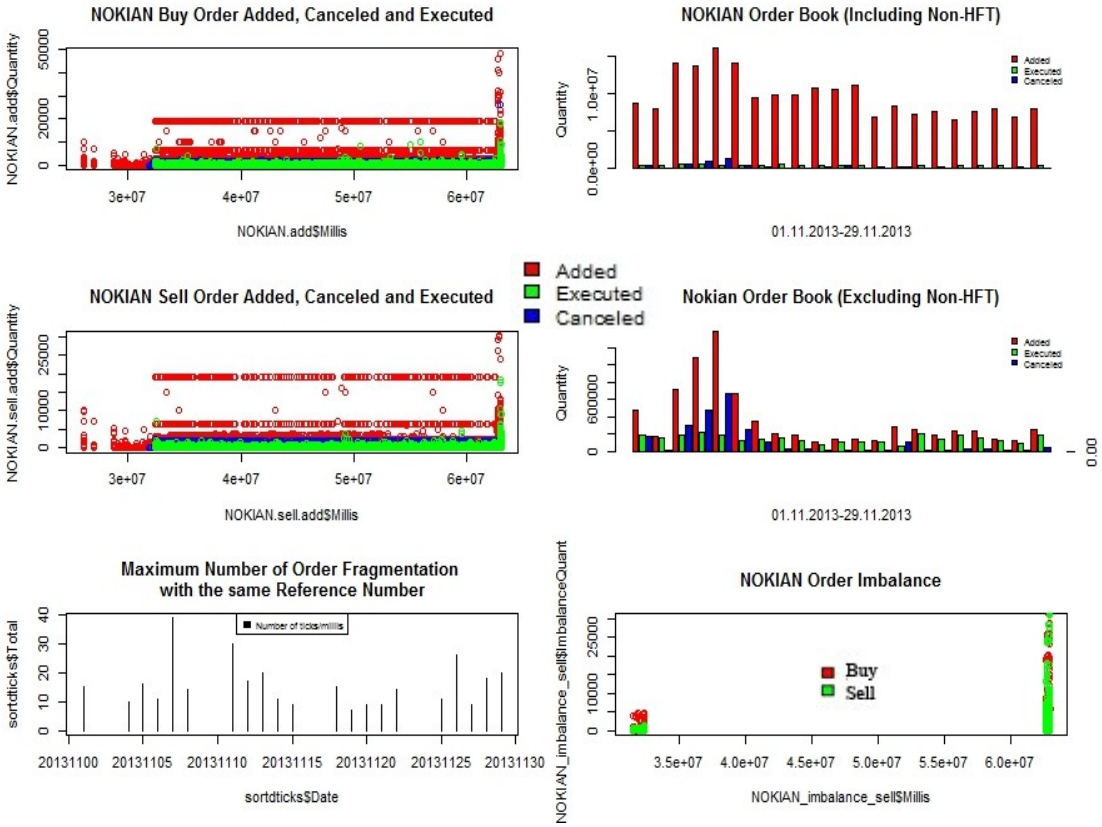

Figure 10: ***Basic LOB activities of NOKIAN for the month of Nov 2013***

The above graph shows that stocks of Nokina Tires are also preferred by the HFT firms. Unlike other stocks, here the quantity of the added buy and sell orders decreased to the level below 25,000 shares. The cancellation and execution percentage seems equal before removing the non-HFT activities, but after removing the non-HFT activities from the LOB the cancellation percentage is barely visssible in most of the trading days.

The average order duration of Nokian in HFT LOB is around 2.09 seconds. There is clear number of order imbalance of Nokian but the number of imbalance is not so huge in comparision to the imbalance of previous stocks. Order imbalance is higher at the end of the trading day. Imbalance is similar for both buy and sell side. Order fragmentation pattern is different for all trading days. *(See Appendix 1 for highest order fragmentation pattern of Nokian from a particular investor).*

- **Outokumpu:** Outokumpu is one of the major producers of stainless steel with its headquarters in Espoo. (www.outokumpu.com).

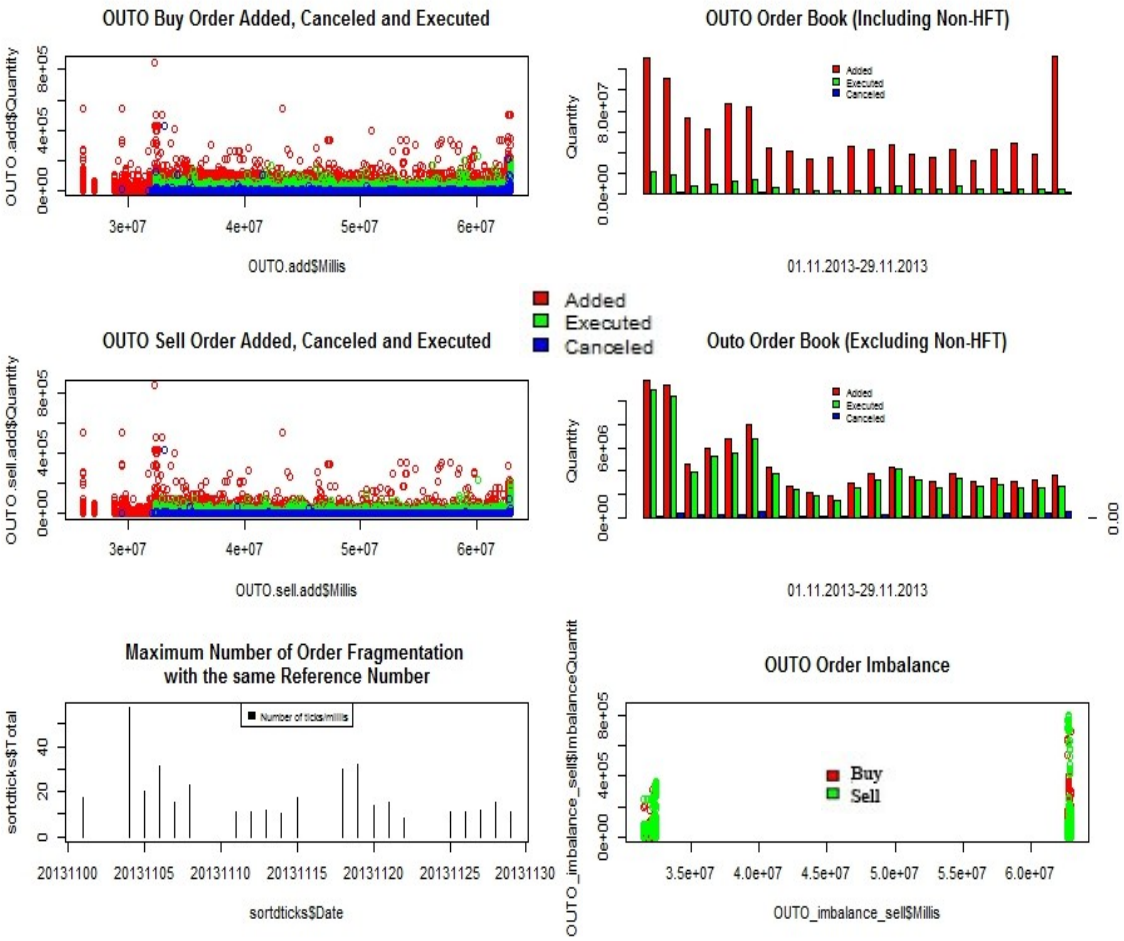

Figure 11: ***Basic LOB activities of OUTOKUMPU for the month of Nov 2013***

There is a very less impact of HFT in LOB activities of Outokumpu. No any pattern is vissible in the buy and sell order. The ratio of share cancellation and execution seems to be equal for this stock as well befroe excluding the non-HFT activities from the LOB. After excluding the non-HFT activities from the LOB the execution percentage almost equals the percentage of share added. The cancellation percentage seems unnoticeable. The average order duration of Outokumpu in HFT LOB is 39.55 seconds, which is quite higher in comparision to previous stocks. Order imbalance is high in both the ends. There is almost equal number of buy and sell orders left at the end of the trading day to carry forward to the next trading days. Similarly there is imbalance at the beginning of the trading day as well. The order fragmentation pattern is mixed and fragmentation in between 20 and 60. *(See Appendix 1 for highest order fragmentation pattern of Outokumpu from a particular investor).*

4.3 Empirical Findings

There is high frequency effect in top three highly liquid stocks where the most of the orders are cancelled before execution. For remaining three stocks there is less high frequency activities where most of the added limit orders are executed without cancelling as well as most of the added order are neither cancelled nor executed.

High frequency activities are differentiated based on the order generating and executing pattern. If an order is made and executed or deleted without any fragmanted order then the order is taken as an ordinary order. In simple term that order which order reference number is duplicated more than one time then the order is supposed to be a high frequency order.

The highest number of orders fragmented sharing the same reference number in limit order book in that particular business day for one month. For example; Stora's added order with same reference number is fregmented to 32 other orders further cancelled and executed sharing the same reference number. First an order is added where 93.5% of orders are deleted and 6.5% of orders are executed (*see Appendix 1*). In market micro structure order imbalance has huge impact in price. Some times price reversal strategy works better if the high frequency trading firm creates huge order imbalance. If the imbalance is on buy side then the the price of the stock might increase for the short period of time which only high frequency traders can capture. Similarly if the order is imbalance on the sell side then the price of the stock will decrease for the short period of time.

Nokia and Nordea have similar order generating patterns. It seems like high frequency traders treat these both stocks in a similar manner. Sixth highly traded stock has less effect from high frequency traders. Execution rate and cancellation rate is very low. Preference of high frequency traders seems on the top five highly liquid stocks. Median shows the order duration in limit order book before the order is either cancelled or executed. The lowest duration is for Nordea, which is just 1.69 second. Event driven is basically theoretical. Traders take a look at the major activities of that particular company and compare the trading pattern with the market news and the business condition of the company and trade accordingly. (Aldridge, 2009) suggest an hourly holding period of the position if any event occurred in that particular firm.

Table: I

Panel A:Holding Period < 1 Minutes (Market Making Strategy)

Stock		Nokia	Stora	Nordea	Metso	Nokian	Outokumpu
Intercept (α)		-0.0062	0.0014	0.0108	0.0046	0.0312	-0.0018
(se)		0.0084	0.007	0.0078	0.0558	0.054	0.0028
(P-value)		(< 1.96)	(< 1.96)	(< 1.96)	(< 1.96)	(< 1.96)	(< 1.96)
Sharpe Ratio	**Non-HFT**	-0.1107	0.0229	0.1758	0.0152	0.0899	-0.1645
	HFT	0.838	0.8382	0.9581	0.9875	0.9051	1.2539
Sortino Ratio	**Non-HFT**	-0.1734	0.0124	0.2941	0.0196	0.1667	-0.3131
	HFT	∞	∞	∞	∞	∞	70.5939
Omega	**Non-HFT**	0.6818	1.0248	1.59	1.0338	1.2847	0.5436
	HFT	∞	∞	∞	∞	∞	290.6073
Kappa	**Non-HFT**	-0.3182	0.0248	0.59	0.0338	0.2847	-0.4569
	HFT	∞	∞	∞	∞	∞	289.6073
VAR		-0.08	-0.1	-0.085	-0.44	-0.42	-0.0174
C.VAR		-0.131	-0.1396	-0.1072	-0.5219	-0.5082	-0.0213

Panel B: Autoregressive Based Test of Market Inefficiency

Restricted Alpha	-0.0062	0.0014	0.0108	0.0046	0.0311	-0.0018
(se)	0.0007	0.0009	0.0011	0.0031	0.0038	-0.0001
R-Squared (Res)	0	0	0	0	0	0
R-Squared (Unres)	0.7779	0.6439	0.6464	0.8356	0.7674	0.9505
AIC (Res)	-18934.05	-13654.77	-9278.31	3984.9	6401.04	-34258.71
AIC (Unres)	-28602.6	-18848.72	-12767.65	-12481.07	-6611.8	-50924.95
Market Inefficiency	1	1	1	1	1	1

	Average		**HFT Times of**
	Non-HFT	**HFT**	**Non-HFT**
Sharpe Ratio	0.004767	0.96	201.4

This table reports the calculation based on the assumptions of 0% Risk free rate, 0% Loss threshold and 0% Minimum acceptable return on the data from NASDAQ OMX Nordic for the month of November 2013. Confidence level is default to p=0.95

'na'- Calculations shows unreliable result

'∞' - Calculations shows infinite result

'Unres'- Unrestricted

'Res'- Restricted

Market making strategy is also known as the liquidity provision which is a mechanism of generating profit from bid and asks spread of the securities. For non-HFT traders it is beyond the capacity to capture the spread in case of highly liquid stocks where the ticks are generating in less than a second time interval. HFT traders have speed advantages that they can capture the bid-ask spread if the they can make profit out of it after deducting all the transactions costs.

In the above table, Table: I, the intercept of bid-ask spread of the time series is negative for Nokia and Outokumpu. In a normal market where bid ask spread is usually positive, in cross market the spread becomes negative so many times. This condition occurs in a highly liquid and volatile market where usually large volumes of stocks are traded. This unusual market situation happens mainly in NASDAQ exchange where a huge amount of orders are entered before the opening bell. Bid ask spread is so tight due to HFT activities. This is why it is difficult to earn statistically significant alpha even for the high frequency traders. Non-HFT traders can capture this spread only in less liquid stocks but usually the bid-ask price is set in such a way that the spread gained will be deducted by the transaction fees.

Even though it is difficult to earn bid ask spread from the market for both the HFT and non-HFT traders the autoregressive based test of market inefficiency of 1 shows that the market is inefficient as there is strong influence of past return in current market return. The Akaike Information Criterion (AIC) is a measure of the quality of model for the given series. It helps in comparing in the goodness of fit between different models. Here, the AIC of unrestricted model is smaller than the AIC of restricted model which suggest that the unrestricted model is better in defining the data sets.

The negative value of Value at Risk (VAR) and Conditional Value at Risk (CVAR) implies that the stocks have probability of making profit. Some of the ratios for HFT traders are infinitive because of 0% risk free rate, 0% loss threshold and 0% minimum acceptable return. Average Sharpe ratio shows that the reward risk ratio of market making strategy of Non-HFT traders is very low. Where, the average Sharpe ratio of HFT trader is close to the market's ratio of one. In market making strategy the average Sharpe ratio of HFT traders is 200 times of the non-HFT traders.

Table: II

Panel A:Holding Period < 10 Minutes (Market Micro Structure Strategy)

Stock		Nokia		Stora		Nordea		Metso		Nokian		Outokumpu	
Position		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
Intercept (α)		0.2544	0.2495	0.3522	0.3388	-0.1443	-0.15	0.8731	0.9286	0.4944	0.5103	-0.0207	-0.0167
(se)		0.0457	0.0714	0.0896	0.111	0.1638	0.1157	0.1452	0.1668	0.1661	0.2727	0.005	0.0051
(P-value)		5.57	3.5	3.93	3.05	(< 1.96)	(< 1.96)	6.01	5.56	2.98	(< 1.96)	(< 1.96)	(< 1.96)
Sharpe Ratio	**Non-HFT**	2.1692	2.15	2.3597	2.2324	-1.0602	-0.9527	2.2609	2.3844	1.0176	1.0626	-1.6854	-1.2614
	HFT	2.3477	2.3648	2.3676	2.2562	1.2268	1.5539	2.7288	2.8344	1.5137	1.5643	1.2675	1.2422
Sortino Ratio	**Non-HFT**	71.561	30.9051	934.9635	59.4226	-0.7373	-0.7017	27.6874	20.7508	3.8784	3.6244	-0.879	-0.8209
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	105.0786	139.2368
Omega	**Non-HFT**	628.8347	422.5595	40599.08	2816.687	0.0612	0.0818	168.1531	200.4685	14.6303	15.8935	0.0342	0.0636
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	469.6071	904.4332
Kappa	**Non-HFT**	627.8347	421.5595	40598.08	2815.687	-0.9388	-0.9181	167.1531	199.4685	13.6303	14.8935	-0.9658	-0.9364
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	468.6071	903.4332
VAR		na	-0.002	na	na	-0.425	-0.4	-0.0641	-0.0501	-0.33	-0.3	-0.0347	-0.0325
C.VAR		na	-0.0029	na	na	-0.4446	-0.4246	-0.0832	-0.0574	-0.5115	-0.5376	-0.0361	-0.0346

Panel B: Autoregressive Based Test of Market Inefficiency

Restricted Alpha	0.2544	0.2495	0.3523	0.339	-0.1443	-0.15	0.8732	0.9286	0.4944	0.5103	-0.207	-0.0167
(se)	0.0014	0.0014	0.0021	0.0021	0.0027	0.0027	0.004	0.0041	0.005	0.0051	-0.0002	-0.0002
R-Squared (Res)	1.11E-16	0	0	-1.11E-16	0	0	0	-1.11E-16	0	0	-4.44E-16	-3.51E-10
R-Squared (Unres)	0.9655	0.9878	0.9536	0.9851	0.9767	0.968	0.9547	0.9507	0.9327	0.95	0.9738	0.9878
AIC (Res)	-9737.25	-9456.41	-4973.21	-4.71E+03	-2803.38	-2896.13	8547.6	8699.99	13151.3	12240.45	-33091.52	-32270.9
AIC Unres)	-32450.47	-37798.16	-20769.5	-25956.87	-15464.18	-14487.25	-19692.49	-18774	-12263.09	-14521.43	-53294.26	-56715.6
Market Inefficiency	1	1	1	1	1	1	1	1	1	1	1	1

	Average		HFT Times
Sharpe Ratio	**Non-HFT**	**HFT**	**of Non-HFT**
Long	0.84	1.91	2.27
Short	0.94	1.97	2.1

This table reports the calculation based on the assumptions of 0% Risk free rate, 0% Loss threshold and 0% Minimum acceptable return on the data from NASDAQ OMX Nordic for the month of November 2013. Confidence level is default to p=0.95

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Market microstructure has been changed in recent years creating more opportunities for HF traders. HF traders can make profit from large buy and sell side orders. They can detect large pool of orders and they can anticipate the change and make profit accordingly. Price reversal strategy is one of the market micro structure strategies where the traders will try to reverse the price of the security by cancelling the large portion of their orders and by creating order imbalance. There is huge order imbalance in all the securities at the very beginning of opening and closing bell.

In the above Table II, investors have the option either to go long or short following that particular strategy. The holding period of the position is typically lesser than 10 minutes for the market micro structure trading strategy. Half of the stocks have positive and highly significant alpha. Sharpe ratio of Nokia, Stora Enso and Metso for HFT and non-HFT traders is almost the same but for other stocks it is almost double of non-HFT. Most of the ratios for HFT traders are infinitive because of same reason as discussed in previous table.

Similarly the negative value of VAR and CVAR implies that the stocks have high probability of generating profit. In a trading of highly volatile stocks, any traders can generate profit from either long or short positions if the stock has a very short holding period, since stock price keeps moving ups and downs in every ticks. Sharpe, Omega and Kappa for Stora's long and short positions are very high for non-HFT traders as well. While doing stock selection, non-HFT traders can choose Stora if they want to get similar ratios as HFT traders do, in average. Stocks having positive Sharpe ratios for non-HFT traders have similar Sharpe ratios for HFT traders as well, but for those with negative ratios for non-HFT traders have almost double positive ratios for HFT traders.

The autoregressive based test of market inefficiency shows the similar result in this strategy as well. It shows that market is inefficient as there is a huge dependence of returns with its lags. Unrestricted R-squared and AIC here show that the unrestricted autoregressive models best defines the return series than the restricted models. The average Sharpe ratio of the HFT and non-HFT traders are similar for both long and short positions but Sharpe for HFT is more than double of non-HFT traders. Market microstructure trading strategies worked at least for 58% of positions in generating significant alpha.

Table: III

Panel A:Holding Period < 1 Hour (Event Trading Strategy)

Stock		Nokia		Stora		Nordea		Metso		Nokian		Outokumpu	
Position		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
Intercept (α)		0.1944	0.2195	0.2572	0.2488	-0.1693	-0.18	1.1731	1.6686	0.6544	0.6903	-0.026	-0.0275
(se)		0.0457	0.0714	0.0896	0.111	0.1638	0.1157	0.1452	0.1668	-0.1661	0.2727	-0.005	0.0051
(P-value)		4.25	3.07	2.87	2.24	(< 1.96)	(< 1.96)	8.08	10	3.94	2.53	(< 1.96)	(< 1.96)
Sharpe Ratio	**Non-HFT**	1.6529	1.8915	1.7234	1.6398	-1.0603	-1.1432	3.0376	3	1.3469	1.4389	-2.1168	-2.0779
	HFT	2.1766	2.25705	1.7806	1.7316	1.2268	1.5772	3.0656	3.093	1.76	1.8728	1.5485	1.5236
Sortino Ratio	**Non-HFT**	13.4401	19.2403	44.8946	23.7564	-0.7373	-0.7587	1820.237	38.6	7.6595	6.7802	-0.914	-0.9102
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	103.1029	70.2015
Omega	**Non-HFT**	57.6548	132.2707	514.838	259.8272	0.0612	0.0435	65021.91	1185.008	32.763	37.1141	0.018	0.017
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	502.7978	318.0744
Kappa	**Non-HFT**	56.6548	131.2707	513.838	258.8272	-0.9388	-0.9565	65020.91	1184.008	31.7629	36.1141	-0.982	-0.983
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	501.7978	317.0744
VAR		-0.025	na	-0.18	-0.01	-0.425	-0.43	na	na	-0.17	-0.12	-0.04	-0.0433
C.VAR		-0.0591	-0.0329	-0.26	-0.0141	-0.4446	-0.4546	na	na	-0.3515	-0.3576	-0.0414	-0.0454

Panel B: Autoregressive Based Test of Market Inefficiency

Restricted Alpha		0.1944	0.2195	0.2573	0.249	-0.1696	-0.18	1.1732	1.1686	0.6544	0.6903	-0.026	-0.0275
(se)		0.0014	0.0014	0.0021	0.0021	0.0027	0.0027	0.004	0.0041	-0.005	-0.0051	-0.0002	-0.0002
R-Squared (Res)		0	0	0	0	0	0	0	0	0	0	-4.44E-16	-3.50E-10
R-Squared (Unres)		0.9655	0.9878	0.9536	0.9851	0.9767	0.9678	0.9547	0.9507	0.9327	0.95	0.9738	0.9878
AIC (Unres)		-32450.5	-37798.2	-20769.5	-25956.9	-15464.18	-14487.25	-19692.49	-18773.99	-12263.09	-14521.43	-53294.26	-56715.56
AIC (Res)		-9737.25	-9456.41	-4973.21	-4707.3	-2803.38	-2896.13	8547.6	8699.99	13151.3	12240.45	-33091.52	-32270.89
Market Inefficiency		1	1	1	1	1	1	1	1	1	1	1	1

This table reports the calculation based on the assumptions of 0% Risk free rate, 0% Loss threshold and 0% Minimum acceptable return on the data from NASDAQ OMX Nordic for the month of November 2013. Confidence level is default to p=0.95

'na'- Calculations shows unreliable result

'∞' - Calculations shows infinite result

'Unres'- Unrestricted

'Res'- Restricted

	Average		HFT Times
Sharpe Ratio	**Non-HFT**	**HFT**	**of Non-HFT**
Long	0.76	1.92	2.53
Short	0.79	2.01	2.54

Event trading is also known as directional trading or news based trading with a typical holding period lesser than one hour. Every hour and every day there will be some kind of news in the media that either directly or indirectly affects the stock price and creates certain movements in the market price.

In the above Table III, investors can go short if they find that the news has negative impact on the share price or they can go long if they think that the news has the positive impact on the share price. The above table assumes that there will be some kind of news in less than every hour which directly or indirectly affects the price movements in both directions.

Event trading strategy is able to generate significant alpha for most of the stocks except Nordea and Outokumpu for both the long and short positions. P-values are significantly high for most of the excess return generated by the event trading strategy. All of the ratios of non-HFT are also higher than of the market. Metso has the highest Sharpe ratio for both long and short position where as Outokumpu and Nordea has negative Sharpe ratio for non-HFT traders and positive for HFT traders. The negative VARs and CVARs show that there is a high chance of profitability for overall traders who are following event trading strategy in their trading. The average Sharpe ratio for HFT traders is two and half times more than that of non-HFT traders.

The autoregressive test of market inefficiency gives 1 as a result, which suggest that market is inefficient and there is strong influence of past returns or past price movements to the current market return for all the stock in both positions. The ACI value of unrestricted model is significantly lower than the restricted with high R-squared value signifying the autocorrelation between the current and the past returns.

Since other ratios give infinite results for the HFT traders, Sharpe ratio here plays an important role in differentiating the performance capacity of HFT and non-HFT that are following the same strategy for the trading. In the event trading non-HFT traders are unable to differentiate good news from the bad news. They do not go into the core of news and trade with bias whereas most of the HFT traders have reliable source of news as they make lots of expenses in getting fresh news from the market. Here event trading strategy of HFT is able to generate significant excess return on 66.67% of positions.

Table: IV

Panel A:Holding Period < 1 Day (Statistical Arbitrage Strategy)

Stock		Nokia		Stora		Nordea		Metso		Nokian		Outokumpu	
Position		Long	Short	Long	Short	Long	Short	Long	Short	Long	Short	Long	Short
Intercept (α)		0.2044	0.2195	0.1922	0.2438	0.2243	0.255	0.9231	0.9286	0.9444	0.8203	-0.0445	-0.0293
(se)		0.0457	0.0714	0.0896	0.111	0.1638	0.1157	0.1452	0.1668	0.1661	0.2727	0.005	0.0051
(P-value)		4.47	3.07	2.145	2.2	(< 1.96)	2.20	6.36	5.57	5.67	3	(< 1.96)	(< 1.96)
Sharpe	**Non-HFT**	1.7379	1.8915	1.288	1.6068	1.4047	1.6195	2.3903	2.3848	1.9437	1.7098	-3.6227	-2.214
	HFT	2.2329	2.2505	1.6	1.7158	0.6324	1.8515	2.8045	2.8345	2.1615	2.0717	1.6483	1.5941
Sortino	**Non-HFT**	16.8126	19.2403	12.2639	22.2716	0.818	0.852	38.8436	20.7508	32.2465	10.1941	-0.9654	-0.9186
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	23.6455	100.8679
Omega	**Non-HFT**	77.1848	132.2707	52.581	230.2508	0.0148	0.0046	271.3426	200.4685	236.8129	73.8603	0.0008	0.0136
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	97.2056	594.8256
Kappa	**Non-HFT**	76.1848	131.2707	51.581	229.2508	0.9852	0.9954	270.3426	199.4685	235.8129	72.8603	-0.9992	-0.9864
	HFT	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	96.2056	593.8256
VAR		-0.015	na	-0.03	-0.001	-0.48	-0.505	-0.02946	-0.0539	-0.06	-0.217	-0.0585	-0.0451
C.VAR		-0.0491	-0.0329	-0.0627	-0.0191	-0.5	-0.5296	-0.0332	-0.0574	-0.0615	-0.2276	-0.0599	-0.048

Panel B: Autoregressive Based Test of Market Inefficiency

Restricted Alpha	0.2044	0.2195	0.1923	0.244	0.2243	0.255	0.9232	0.9286	0.9444	0.8203	-0.0445	-0.0293
(se)	0.0014	0.0014	0.0021	0.0021	0.0027	0.0027	-0.004	-0.0041	-0.005	-0.0051	0.0002	0.0002
R-Squared (Res)	0		0	0	0	0	0	-1.11E-16	0	0	-2.22E-16	-3.51E-10
R-Squared (Unres)	0.9655	0.9878	0.9536	0.9851	0.9767	0.968	0.9547	0.9507	0.9327	0.95	0.9738	0.9878
AIC (Res)	-9737.25	-37798.16	-4973.21	-4707.3	-2803.38	-2896.13	8547.6	8699.99	13151.3	12240.45	-33091.52	-32270.89
AIC (Unres)	-32450.47	-9456.41	-20769.5	-25956.87	-15464.18	-14487.25	-19692.49	-18773.99	-12263.09	-14521.43	-53294.26	-56715.56
Market Inefficiency	1	1	1	1	1	1	1	1	1	1	1	1

This table reports the calculation based on the assumptions of 0% Risk free rate, 0% Loss threshold and 0% Minimum acceptable return on the data from NASDAQ OMX Nordic for the month of November 2013. Confidence level is default to p=0.95

'na'- Calculations shows unreliable result

'∞' - Calculations shows infinite result

'Unres'- Unrestricted

'Res'- Restricted

	Average		HFT Times
Sharpe Ratio	**Non-HFT**	**HFT**	**of Non-HFT**
Long	0.39	1.85	4.75
Short	0.63	2.05	3.28

Statistical arbitrage strategy is the quantitative strategy and HFT applies these types of quantitative strategy in a fraction of second. Statistical arbitrage is one of the most used strategies from the HFT firms. There are various kinds of Statistical arbitrage strategies which can be used by non-HFT firms as well. Holding the long position of one security and continuously shorting the negatively correlated security or holding the short position the other way around is one kind of market neutral statistical arbitrage strategy. Settling the position before the end of trading day is necessary for HF traders. Non-HFT traders can hold the position for longer period as well. The holding period of the security following statistical arbitrage strategy is generally less than a day.

In the above Table IV, all the stocks have both the long and short positions where the alpha for most of the stocks are statistically significant, Nordea in long position and Outokumpu in both position fail to provide alpha for the traders in statistical arbitrage strategy. Sharpe ratio is slightly higher for positive positions comparing HFT and non-HFT both the long and short positions. P-values are significantly higher than the critical value for most of the excess return generated by the statistical arbitrage strategy. All of the ratios of non-HFT traders following statistical arbitrage strategy are also higher than of the market. Metso has the highest Sharpe ratio for both long and short position. The negative VARs and CVARs show that there is a high chance of profitability for overall traders who are following statistical arbitrage strategy in their trading. The average Sharpe ratio for HFT traders is almost 5 times higher than that of non-HFT traders. Short position holdings is providing higher Sharpe ratio than the long holdings. The autoregressive test of market inefficiency suggests that market is inefficient and there is strong influence of past returns or past price movements to the current market return for all the stocks, in both positions. The ACI value of unrestricted model is significantly lower than the restricted with high R-squared value signifying the time dependences.

Statistical arbitrage strategy worked here for 75% of the positions. Non-HFT traders following statistical arbitrage can generate equivalent amount of return in respect to the risk taken by them. The difference between the ratios is not too high between HFT and non-HFT but in average while including the loosing stocks, it drastically decreased the Sharpe ratio of the non-HFT traders making almost 5 times lower than that of HFT traders.

5. CONCLUSION

The purpose of this thesis was to implement the HFT strategies in Finnish stock market with the main research problem of finding the performance capacity of those applied strategies suggested by Aldridge (2009). Performance capacity is measured based on the comparative ratios and autoregressive based test of market inefficiency.

For the main research question about the performance capacity of HFT strategies in Finnish stock market, the capacity is high, except for market making strategy. Market Making Strategy is unable to provide statistically significant alpha for all the selected stocks. It is because of very tight bid and ask spread as stocks selected for this study are highly liquid and highly traded. Traders might get alpha on less liquid stocks, Sharpe ratio is equal to market for HFT and very less for non HFT traders, negative VAR signifies possibility of positive return. Market Micro Structure Strategy provides similar return for both HFT and non HFT traders with average success rate in generating statistically significant alpha. Event Trading Strategy provides little bit higher return to HFT traders with higher success rate than those, using micro structure strategy. Statistical Arbitrage Strategy with the highest success rate is the best among these four strategies with highly significant alpha. Sharpe ratio for average non-HFT traders is below market whereas Sharpe ratio for HFT traders is double of the market.

The result of this thesis matches to the findings by Hendershott and Riordan (2009) who used NASDAQ data for the analysis, excluding the sixth less liquid stock (Outokumpu) from the calculation list. LOB activities also show less influence of HFT traders on Outokumpu. Considering only top five highly traded stocks gives cent percent performance accuracy for statistical arbitrage strategy, as well as increasing accuracy of other strategies. Sometimes most of the strategies works for same stocks and sometimes all the strategies are unable to generate statistically significant alpha, signifying the importance of market timing and stock selection.

The additional research questions on Finnish stock market inefficiency, based on autoregressive test of market inefficiency shows Finnish stock market is inefficient. There is high dependences between the lags, suggesting unrestricted model to be preferred over restricted in defining the data sets. Strategies are efficient but the market is inefficient, making the traders following statistical arbitrage strategy to

generate alpha very easily from the trading. Same strategy is not profitable for all the stocks. Thesis analysis shows that the loss in one position following one strategy can be overcome by following another strategy. Timing as well as stock selection plays the vital role in generating alpha. Yes, the strategies are time dependent. Same strategy for all the stocks for all the time does not work. So, we cannot reject our null hypothesis that, HFT strategies are dependent on the timing and the stock selection as profit generated using same strategy for all the stocks at all times is not statistically significant.

The main limitation with this thesis is the use of selective stocks with one month data to draw the conclusion from. Use of longer evaluation period and including most of the stocks with even minimum influence from HFT traders will provide more accurate result. Another limitation was huge data handling using personal computer, which was difficult and time consuming.

The result of this thesis is beneficial to both the academic and non-academic professionals who have interest on HFTs. Academic person can further analyze the similar approach with longer time length and take more stocks into consideration. For non-academic professionals who are active in HFT trading, it gives clear picture on how to use the HFT strategies and how to evaluate its performance. Those HFT firms who cannot invest high amount of money to get news feed micro second sooner than their competitors can use the similar strategies to generate significant alpha from the trading. It is also useful to the newly started HFT firms who are wondering what strategy to use with what holding period.

Following the similar approach, someone willing to carryout research for different market or same market with different securities can do further study on this subject matter. This thesis uses the strategies suggested by Aldridge (2009), however anyone willing to carryout similar study can use the strategies suggested by SEC (Security Exchange Commission) as least profitable, most profitable and constructive, less constructive strategies. They can follow the strategies suggested by any other scholars in HFT. Finally to conclude, speed is not a strategy but one of the advantages to generate profit in HFT. Efficient HFT strategy with wise stock selection and effective market timing is the most important tool in HFT to generate significant profit in any market situation.

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APPENDIX

Appendix 1: Highest Order Fragmentations

Nokia's highest order fragmentation pattern from a particular investor

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009000681	96981	S	5.79	32395284	A	21000	20131120
FI0009000681	96981	S	5.79	32400426	E	405	20131120
FI0009000681	96981	S	5.79	32400426	E	40	20131120
FI0009000681	96981	S	5.79	32400426	E	20	20131120
FI0009000681	96981	S	5.79	32400426	E	350	20131120
FI0009000681	96981	S	5.79	32400426	E	3	20131120
FI0009000681	96981	S	5.79	32400426	E	5	20131120
FI0009000681	96981	S	5.79	32400426	E	7	20131120
FI0009000681	96981	S	5.79	32400426	E	50	20131120
FI0009000681	96981	S	5.79	32400426	E	427	20131120
FI0009000681	96981	S	5.79	32400426	E	35	20131120
FI0009000681	96981	S	5.79	32400426	E	5	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120
FI0009000681	96981	S	5.79	32400426	E	60	20131120
FI0009000681	96981	S	5.79	32400426	E	2	20131120
FI0009000681	96981	S	5.79	32400426	E	10	20131120
FI0009000681	96981	S	5.79	32400426	E	2000	20131120
FI0009000681	96981	S	5.79	32400426	E	1000	20131120
FI0009000681	96981	S	5.79	32400426	E	40	20131120
FI0009000681	96981	S	5.79	32400426	E	22	20131120
FI0009000681	96981	S	5.79	32400426	E	200	20131120
FI0009000681	96981	S	5.79	32400426	E	80	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120
FI0009000681	96981	S	5.79	32400426	E	140	20131120
FI0009000681	96981	S	5.79	32400426	E	300	20131120
FI0009000681	96981	S	5.79	32400426	E	300	20131120
FI0009000681	96981	S	5.79	32400426	E	200	20131120
FI0009000681	96981	S	5.79	32400426	E	55	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	110	20131120
FI0009000681	96981	S	5.79	32400426	E	50	20131120
FI0009000681	96981	S	5.79	32400426	E	300	20131120
FI0009000681	96981	S	5.79	32400426	E	40	20131120
FI0009000681	96981	S	5.79	32400426	E	400	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	30	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120

FI0009000681	96981	S	5.79	32400426	E	91	20131120
FI0009000681	96981	S	5.79	32400426	E	10	20131120
FI0009000681	96981	S	5.79	32400426	E	200	20131120
FI0009000681	96981	S	5.79	32400426	E	300	20131120
FI0009000681	96981	S	5.79	32400426	E	687	20131120
FI0009000681	96981	S	5.79	32400426	E	1700	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120
FI0009000681	96981	S	5.79	32400426	E	110	20131120
FI0009000681	96981	S	5.79	32400426	E	50	20131120
FI0009000681	96981	S	5.79	32400426	E	200	20131120
FI0009000681	96981	S	5.79	32400426	E	82	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	25	20131120
FI0009000681	96981	S	5.79	32400426	E	600	20131120
FI0009000681	96981	S	5.79	32400426	E	1294	20131120
FI0009000681	96981	S	5.79	32400426	E	1029	20131120
FI0009000681	96981	S	5.79	32400426	E	250	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	1000	20131120
FI0009000681	96981	S	5.79	32400426	E	150	20131120
FI0009000681	96981	S	5.79	32400426	E	500	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	9	20131120
FI0009000681	96981	S	5.79	32400426	E	1	20131120
FI0009000681	96981	S	5.79	32400426	E	19	20131120
FI0009000681	96981	S	5.79	32400426	E	300	20131120
FI0009000681	96981	S	5.79	32400426	E	100	20131120
FI0009000681	96981	S	5.79	32400426	E	250	20131120
FI0009000681	96981	S	5.79	32400426	E	2057	20131120

Order Added: 100%

Order Cancelled: 0%

Order Executed: 100%

Position: Short

Number of fragmentations: 70

Order Duration: 5142 Milliseconds (5 seconds)

Nordea's highest order fragmentation pattern from a particular investor

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009902530	2035889	S	9.305	36870491	A	50925	20131111
FI0009902530	2035889	S	9.305	36870492	X	2000	20131111
FI0009902530	2035889	S	9.305	36870492	X	1565	20131111
FI0009902530	2035889	S	9.305	36870516	X	400	20131111
FI0009902530	2035889	S	9.305	36870516	X	800	20131111
FI0009902530	2035889	S	9.305	36870517	X	3018	20131111
FI0009902530	2035889	S	9.305	36870517	X	2400	20131111
FI0009902530	2035889	S	9.305	36870548	X	1300	20131111
FI0009902530	2035889	S	9.305	36870646	X	800	20131111
FI0009902530	2035889	S	9.305	36870648	X	2400	20131111
FI0009902530	2035889	S	9.305	36870672	X	1000	20131111
FI0009902530	2035889	S	9.305	36870731	X	450	20131111
FI0009902530	2035889	S	9.305	36870948	X	8861	20131111
FI0009902530	2035889	S	9.305	36874560	X	7662	20131111
FI0009902530	2035889	S	9.305	36874560	X	473	20131111
FI0009902530	2035889	S	9.305	36874560	X	1312	20131111
FI0009902530	2035889	S	9.305	36876186	X	1354	20131111
FI0009902530	2035889	S	9.305	36876186	X	2000	20131111
FI0009902530	2035889	S	9.305	36876186	X	550	20131111
FI0009902530	2035889	S	9.305	36887554	X	32	20131111
FI0009902530	2035889	S	9.305	36887604	X	100	20131111
FI0009902530	2035889	S	9.305	36887604	X	100	20131111
FI0009902530	2035889	S	9.305	36887706	X	900	20131111
FI0009902530	2035889	S	9.305	36887755	X	200	20131111
FI0009902530	2035889	S	9.305	36887805	X	200	20131111
FI0009902530	2035889	S	9.305	36887807	X	1300	20131111
FI0009902530	2035889	S	9.305	36887855	X	141	20131111
FI0009902530	2035889	S	9.305	36887855	X	59	20131111
FI0009902530	2035889	S	9.305	36887944	X	200	20131111
FI0009902530	2035889	S	9.305	36887994	X	200	20131111
FI0009902530	2035889	S	9.305	36887994	X	1500	20131111
FI0009902530	2035889	S	9.305	36888044	X	200	20131111
FI0009902530	2035889	S	9.305	36888130	X	200	20131111
FI0009902530	2035889	S	9.305	36888179	X	200	20131111
FI0009902530	2035889	S	9.305	36888229	X	200	20131111
FI0009902530	2035889	S	9.305	36888278	X	200	20131111
FI0009902530	2035889	S	9.305	36888329	X	200	20131111
FI0009902530	2035889	S	9.305	36888379	X	41	20131111
FI0009902530	2035889	S	9.305	36888379	X	159	20131111
FI0009902530	2035889	S	9.305	36888430	X	200	20131111
FI0009902530	2035889	S	9.305	36888480	X	200	20131111
FI0009902530	2035889	S	9.305	36888532	X	200	20131111
FI0009902530	2035889	S	9.305	36888583	X	200	20131111

FI0009902530	2035889	S	9.305	36888633	X	41	20131111
FI0009902530	2035889	S	9.305	36888633	X	159	20131111
FI0009902530	2035889	S	9.305	36888685	X	200	20131111
FI0009902530	2035889	S	9.305	36888735	X	200	20131111
FI0009902530	2035889	S	9.305	36888988	X	153	20131111
FI0009902530	2035889	S	9.305	36889040	X	200	20131111
FI0009902530	2035889	S	9.305	36889090	X	200	20131111
FI0009902530	2035889	S	9.305	36889142	X	200	20131111
FI0009902530	2035889	S	9.305	36889192	X	200	20131111
FI0009902530	2035889	S	9.305	36889192	X	112	20131111
FI0009902530	2035889	S	9.305	36889242	X	200	20131111
FI0009902530	2035889	S	9.305	36889292	X	200	20131111
FI0009902530	2035889	S	9.305	36889342	X	200	20131111
FI0009902530	2035889	S	9.305	36889394	X	200	20131111
FI0009902530	2035889	S	9.305	36889444	X	200	20131111
FI0009902530	2035889	S	9.305	36889494	X	200	20131111
FI0009902530	2035889	S	9.305	36889535	X	837	20131111
FI0009902530	2035889	S	9.305	36889535	X	333	20131111
FI0009902530	2035889	S	9.305	36889545	X	200	20131111
FI0009902530	2035889	S	9.305	36889634	X	200	20131111
FI0009902530	2035889	S	9.305	36889685	X	13	20131111
FI0009902530	2035889	S	9.305	36889685	X	187	20131111
FI0009902530	2035889	S	9.305	36889838	X	100	20131111
FI0009902530	2035889	S	9.305	36889899	X	200	20131111
FI0009902530	2035889	S	9.305	36889949	X	13	20131111
FI0009902530	2035889	S	9.305	36889949	X	187	20131111
FI0009902530	2035889	S	9.305	36890001	X	200	20131111

Order Added: 100%

Order Cancelled: 100%

Order Executed: 0%

Position: Short

Number of fragmentations: 69

Order Duration: 19150 milliseconds (19 seconds)

Stora Enso's highest order fragmentation pattern from a particular investor

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009005961	2341286	S	7.51	38930391	A	36800	20131128
FI0009005961	2341286	S	7.51	38930391	X	800	20131128
FI0009005961	2341286	S	7.51	38930391	X	800	20131128
FI0009005961	2341286	S	7.51	38930391	X	1600	20131128
FI0009005961	2341286	S	7.51	38930391	X	2400	20131128
FI0009005961	2341286	S	7.51	38930392	X	800	20131128
FI0009005961	2341286	S	7.51	38930392	X	800	20131128
FI0009005961	2341286	S	7.51	38930444	X	1600	20131128
FI0009005961	2341286	S	7.51	38930444	X	1600	20131128
FI0009005961	2341286	S	7.51	38930444	X	1600	20131128
FI0009005961	2341286	S	7.51	38930444	X	1600	20131128
FI0009005961	2341286	S	7.51	38939440	X	800	20131128
FI0009005961	2341286	S	7.51	38939440	X	1600	20131128
FI0009005961	2341286	S	7.51	38939440	X	800	20131128
FI0009005961	2341286	S	7.51	38939488	X	800	20131128
FI0009005961	2341286	S	7.51	38939488	X	1600	20131128
FI0009005961	2341286	S	7.51	38939488	X	800	20131128
FI0009005961	2341286	S	7.51	39033220	X	800	20131128
FI0009005961	2341286	S	7.51	39033220	X	1600	20131128
FI0009005961	2341286	S	7.51	39033220	X	800	20131128
FI0009005961	2341286	S	7.51	39033220	X	2400	20131128
FI0009005961	2341286	S	7.51	39033220	X	800	20131128
FI0009005961	2341286	S	7.51	39033220	X	800	20131128
FI0009005961	2341286	S	7.51	39033220	X	800	20131128
FI0009005961	2341286	S	7.51	39040320	X	800	20131128
FI0009005961	2341286	S	7.51	39040574	X	1600	20131128
FI0009005961	2341286	S	7.51	39040985	X	800	20131128
FI0009005961	2341286	S	7.51	39049650	X	800	20131128
FI0009005961	2341286	S	7.51	39065805	X	800	20131128
FI0009005961	2341286	S	7.51	39274016	X	800	20131128
FI0009005961	2341286	S	7.51	39514741	X	800	20131128
FI0009005961	2341286	S	7.51	39658434	E	2400	20131128

Order Added: 100%

Ordered Cancelled: 93.5%

Order Executed: 6.5%

Position: Short

Number of fragmentations: 32

Order Duration: 12 minutes

Metso's highest order fragmentation pattern

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009007835	9497040	S	29.61	62968685	A	40000	20131115
FI0009007835	9497040	S	29.61	62973978	E	2042	20131115
FI0009007835	9497040	S	29.61	62973978	E	3540	20131115
FI0009007835	9497040	S	29.61	62973978	E	100	20131115
FI0009007835	9497040	S	29.61	62973978	E	273	20131115
FI0009007835	9497040	S	29.61	62973978	E	4414	20131115
FI0009007835	9497040	S	29.61	62973978	E	370	20131115
FI0009007835	9497040	S	29.61	62973978	E	480	20131115
FI0009007835	9497040	S	29.61	62973978	E	407	20131115
FI0009007835	9497040	S	29.61	62973978	E	128	20131115
FI0009007835	9497040	S	29.61	62973978	E	12	20131115
FI0009007835	9497040	S	29.61	62973978	E	523	20131115
FI0009007835	9497040	S	29.61	62973978	E	4296	20131115
FI0009007835	9497040	S	29.61	62973978	E	84	20131115
FI0009007835	9497040	S	29.61	62973978	E	274	20131115
FI0009007835	9497040	S	29.61	62973978	E	2577	20131115
FI0009007835	9497040	S	29.61	62973978	E	523	20131115
FI0009007835	9497040	S	29.61	62973978	E	1455	20131115
FI0009007835	9497040	S	29.61	62973978	E	1592	20131115
FI0009007835	9497040	S	29.61	62973978	E	1482	20131115
FI0009007835	9497040	S	29.61	62973978	E	8	20131115
FI0009007835	9497040	S	29.61	62973978	E	81	20131115
FI0009007835	9497040	S	29.61	62973978	E	6177	20131115
FI0009007835	9497040	S	29.61	62973978	E	1110	20131115
FI0009007835	9497040	S	29.61	62973978	E	517	20131115
FI0009007835	9497040	S	29.61	62973978	E	2246	20131115
FI0009007835	9497040	S	29.61	62973978	E	518	20131115
FI0009007835	9497040	S	29.61	62973978	E	517	20131115
FI0009007835	9497040	S	29.61	62973978	E	2059	20131115
FI0009007835	9497040	S	29.61	62973978	E	180	20131115
FI0009007835	9497040	S	29.61	62973978	E	517	20131115
FI0009007835	9497040	S	29.61	62973978	E	1498	20131115

Order Added: 100%

Order Cancelled: 0%

Order Executed: 100%

Position: Short

Number of fragmentations: 33

Order Duration: 5293 milliseconds (5 seconds)

Nokian's highest order fragmentation pattern from a particular investor

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009005318	15950726	B	40.68	62720950	A	28154	20131107
FI0009005318	15950726	B	40.68	62982864	E	1715	20131107
FI0009005318	15950726	B	40.68	62982864	E	326	20131107
FI0009005318	15950726	B	40.68	62982864	E	327	20131107
FI0009005318	15950726	B	40.68	62982864	E	66	20131107
FI0009005318	15950726	B	40.68	62982864	E	408	20131107
FI0009005318	15950726	B	40.68	62982864	E	1014	20131107
FI0009005318	15950726	B	40.68	62982864	E	22	20131107
FI0009005318	15950726	B	40.68	62982864	E	1189	20131107
FI0009005318	15950726	B	40.68	62982864	E	2877	20131107
FI0009005318	15950726	B	40.68	62982864	E	517	20131107
FI0009005318	15950726	B	40.68	62982864	E	15	20131107
FI0009005318	15950726	B	40.68	62982864	E	8876	20131107
FI0009005318	15950726	B	40.68	62982864	E	270	20131107
FI0009005318	15950726	B	40.68	62982864	E	132	20131107
FI0009005318	15950726	B	40.68	62982864	E	145	20131107
FI0009005318	15950726	B	40.68	62982864	E	77	20131107
FI0009005318	15950726	B	40.68	62982864	E	64	20131107
FI0009005318	15950726	B	40.68	62982864	E	231	20131107
FI0009005318	15950726	B	40.68	62982864	E	181	20131107
FI0009005318	15950726	B	40.68	62982864	E	3	20131107
FI0009005318	15950726	B	40.68	62982864	E	2277	20131107
FI0009005318	15950726	B	40.68	62982864	E	1	20131107
FI0009005318	15950726	B	40.68	62982864	E	48	20131107
FI0009005318	15950726	B	40.68	62982864	E	659	20131107
FI0009005318	15950726	B	40.68	62982864	E	445	20131107
FI0009005318	15950726	B	40.68	62982864	E	37	20131107
FI0009005318	15950726	B	40.68	62982864	E	8	20131107
FI0009005318	15950726	B	40.68	62982864	E	901	20131107
FI0009005318	15950726	B	40.68	62982864	E	329	20131107
FI0009005318	15950726	B	40.68	62982864	E	139	20131107
FI0009005318	15950726	B	40.68	62982864	E	842	20131107
FI0009005318	15950726	B	40.68	62982864	E	24	20131107
FI0009005318	15950726	B	40.68	62982864	E	866	20131107
FI0009005318	15950726	B	40.68	62982864	E	334	20131107
FI0009005318	15950726	B	40.68	62982864	E	1132	20131107
FI0009005318	15950726	B	40.68	62982864	E	565	20131107
FI0009005318	15950726	B	40.68	62982864	E	56	20131107
FI0009005318	15950726	B	40.68	62982864	E	343	20131107
FI0009005318	15950726	B	40.68	62982864	E	693	20131107

Order Added: 100%, Order Cancelled: 0%, Order Executed: 100%, Position: long
Number of fragmentations: 40, Order Duration: 4 minutes

Outokumpu's highest order fragmentation pattern from a particular investor

ISIN	OrderRefNo	BuySell	LimitPrice	Millis	Action	Quantity	Date
FI0009002422	115913	S	0.3972	32398217	A	123210	20131104
FI0009002422	115913	S	0.3972	32400413	E	4000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1500	20131104
FI0009002422	115913	S	0.3972	32400413	E	510	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	100	20131104
FI0009002422	115913	S	0.3972	32400413	E	10000	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	150	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1500	20131104
FI0009002422	115913	S	0.3972	32400413	E	100	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	600	20131104
FI0009002422	115913	S	0.3972	32400413	E	250	20131104
FI0009002422	115913	S	0.3972	32400413	E	100	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1227	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	350	20131104
FI0009002422	115913	S	0.3972	32400413	E	350	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	600	20131104
FI0009002422	115913	S	0.3972	32400413	E	3000	20131104
FI0009002422	115913	S	0.3972	32400413	E	10000	20131104
FI0009002422	115913	S	0.3972	32400413	E	3000	20131104
FI0009002422	115913	S	0.3972	32400413	E	4000	20131104
FI0009002422	115913	S	0.3972	32400413	E	6000	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	625	20131104
FI0009002422	115913	S	0.3972	32400413	E	2500	20131104
FI0009002422	115913	S	0.3972	32400413	E	500	20131104

FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	400	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	300	20131104
FI0009002422	115913	S	0.3972	32400413	E	1000	20131104
FI0009002422	115913	S	0.3972	32400413	E	5000	20131104
FI0009002422	115913	S	0.3972	32400413	E	4000	20131104
FI0009002422	115913	S	0.3972	32400413	E	100	20131104
FI0009002422	115913	S	0.3972	32400413	E	2000	20131104
FI0009002422	115913	S	0.3972	32400413	E	10000	20131104
FI0009002422	115913	S	0.3972	32400413	E	700	20131104
FI0009002422	115913	S	0.3972	32400413	E	300	20131104
FI0009002422	115913	S	0.3972	32400413	E	948	20131104

Order Added: 100%

Order Cancelled: 0%

Order Executed: 100%

Position: Short

Number of fragmentations: 61

Order Duration: 2196 milliseconds (2 seconds)