Aalto University
School of Economics

THE ROLE OF HIGH FREQUENCY TRADING IN LIMIT ORDER BOOK ACTIVITY: EVIDENCE FROM HELSINKI STOCK EXCHANGE

Economics

Master's thesis

Antti Tuominen

2012

Department of Economics
Aalto University
School of Economics

Aalto University
School of Economics

Master's Thesis

Antti Tuominen

Abstract

April 23rd, 2012

THE ROLE OF HIGH FREQUENCY TRADING IN LIMIT ORDER BOOK ACTIVITY: EVIDENCE FROM HELSINKI STOCK EXCHANGE

PURPOSE OF THE STUDY

The purpose of this study is to examine the role of high frequency trading in limit order book activity in Helsinki Stock Exchange. This study investigates the degree of high frequency trading in the market place by identifying high frequency trading accounts from limit order data and by looking at their trading behavior with respect to order generation and cancellation dynamics.

DATA

The data used in this study is one week order level data from NASDAQ OMX Nordic Exchange Helsinki for five selected liquid stocks. The order data, which consists of limit orders, cancellations, and executions, is used to build a limit order book that captures the trading mechanism of an electronic order-driven market. The order level data is also used to identify high frequency trading accounts by looking at their order generation characteristics.

RESULTS

This study finds that the limit order books of the sampled stocks are dominated by a handful of high frequency traders employing sophisticated trading algorithms and accessing the market with low-latency connections. The evidence suggests that these traders are responsible for a majority of the order flow and that their order generation is highly periodic. Their order flow dynamics indicate that they often cancel a limit order shortly after placing it, and that their limit order cancellations are followed rapidly by new limit order messages. This study also finds that order flow from high frequency trading accounts has short-term effects on stock price for most of the sampled securities.

KEYWORDS: Algorithmic trading, high frequency trading, limit order book, order flow imbalance, electronic liquidity provision, market microstructure

Aalto Yliopisto

Kauppakorkeakoulu

Pro Gradu -tutkielma | Tiivistelmä

Antti Tuominen | 23. Huhtikuuta 2012

HIGH FREQUENCY – KAUPANKÄYJIEN TOIMINTA HELSINGIN PÖRSSISSÄ

TUTKIELMAN TAVOITTEET

Tutkielman tavoitteena on arvioida ns. High Frequency – kaupankäyjien roolia Helsingin Pörssissä. High Frequency – kaupankäyjien osuutta pörssin toimeksiantojen kokonaismäärästä tutkitaan tunnistamalla High Frequency – kauppaa käyviä kaupankäyntitilejä toimeksiantodatasta ja tutkimalla heidän toimeksiantokäyttäytymistään.

LÄHDEAINESTO

Tutkimuksen aineisto on viiden osakkeen täydellinen toimeksiantodata NASDAQ OMX Nordic Exchange Helsinki – markkinapaikalta yhden viikon ajalta. Toimeksiantodata koostuu toimeksiannoista, peruutuksista sekä kaupoista, ja sen avulla rakennetaan toimeksiantokanta elektronisen toimeksiantopohjaisen markkinapaikan kaupankäyntimekanismien pohjalta.

TULOKSET

Tuloksista käy ilmi että tutkittujen osakkeiden kohdalla toimeksiantokantaa hallitsee pieni joukko aktiivisia High Frequency – kaupankäyjiä, jotka käyttävät kehittyneitä kaupankäyntialgoritmeja ja reagoivat markkinamuutoksiin hyvin pienellä viiveellä. Tulokset osoittavat että nämä kaupankävijät ovat vastuussa suurimmasta osasta toimeksiantoja, ja että niiden toimeksiantokäyttäytymisensä on hyvin jaksottaista. Tutkittujen High Frequency –kaupankävijöiden toimeksiantodynamiikka viittaa siihen, että he usein peruvat asettamansa toimeksiannot välittömästi niiden asettamisen jälkeen. Toisaalta he myös usein asettavat uusia toimeksiantoja välittömästi peruutusten jälkeen. Tutkielman tulokset viittaavat myös siihen että heidän toimeksiantokäyttäytymisensä vaikuttaa pörssikurssiin lyhyellä aikavälillä.

AVAINSANAT: tietokonepohjainen kaupankäynti, high frequency -kaupankäynti, toimeksiantokanta, toimeksiantojen epätasapaino, elektroninen markkinatakaus, markkinamikrostruktuuri

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1. The rise of high frequency trading

The landscape of equity trading has undergone a dramatic change during the previous decades. Traditionally, stock exchanges were organized as floor-based marketplaces where buyers and sellers were represented by intermediaries who arranged the trades between market participants. In the floor-based system, the trading was usually concentrated in a single physical location in any given country, the national stock exchange. Today the old system has given way to electronic trading through different trading venues. This shift has been driven forward by technological development and changes in regulation concerning securities trading (Kirilenko et al., 2011). Advances in trading systems, in the ability of market participants to analyze data, and in the overall technological infrastructure supporting computerized equity trading has created an appealing environment for market participants to develop sophisticated trading strategies that employ sophisticated algorithms. Activity in the limit order books of computerized trading venues is nowadays dominated by the interaction between these algorithms (Hasbrouck & Saar, 2011), yet not so much is known about their exact trading behavior.

High frequency trading is responsible for a major share of the total trading and quote volume in stock exchanges all over the world. The share of high frequency trading of all equity trades has been estimated to account for over 68 per cent of the total dollar volume in the US (Brogaard, 2010b). Given the rapid development in the equities trading industry, these numbers are probably conservative estimates of the share of high frequency trading as of now. The Securities and Exchange Commission recently referred to high frequency trading as “one of the most significant market structure developments in recent years” (SEC, 2010). High frequency trading has drawn significant public attention after the “Flash Crash” on May 6th 2010, and many regulatory bodies are undergoing discussions about imposing rules for high frequency traders (see IOSCO, 2011 for an overview). Regulators are concerned that algorithmic trading, and high frequency trading in particular, may have negative effects on market quality in times of severe market stress, and that high frequency trading deteriorates equality of market participants (Angel & McCabe, 2010).

1.2. Concerns over high frequency trading

There is an ongoing discussion about the merits of high frequency trading. Regulators and market participants have raised a number of concerns about the practices of high frequency traders. One major concern is associated with the fact that high frequency traders are replacing traditional market makers as suppliers of liquidity (Gerig & Michayluk, 2010). High frequency traders acting as electronic liquidity providers (ELPs) have no requirements to maintain a fair and orderly market like their traditional counterparts, nor do they have a minimum amount of shares to provide, or a minimum time to offer a quote (Arnuk & Saluzzi, 2009). ELPs can thus turn off their supply of liquidity at any time, which can have severe effects on market efficiency (Hasbrouck & Saar, 2011). Regulators in Europe and in the US are considering whether high frequency traders should face quotation obligations like those imposed on registered market makers (SEC, 2010).

Another concern associated with high frequency traders comes from their ability to engage in so called predatory activities. High frequency traders can generate false trading signals by using their speed advantage to issue a massive number of orders on one side of the order book and thus change the perceived demand/supply of a stock. This trading strategy, called *layering,* is identified as market abuse in most equity trading venues. On May 6th 2011 The Financial Services Authority (FSA) fined Swift Trade Inc., a Canadian company, for an £8 million penalty for layering in the London Stock Exchange (FSA, 2011). Swift Trade used its speed advantage to place large orders on one side of the book in order to create a signal of a change in the supply/demand of the security, while simultaneously trading on the other side of the book and making a profit from the share price movement. This was followed by rapid deletion of the large initial orders, which were never intended to be traded. Although most high frequency traders presumably do not engage in these activities, the case against Swift Trade shows the extent to which high frequency traders can utilize their speed advantage over other market participants and highlights the need for regulatory review over their practices.

Third area of concern is that high frequency traders can extract surplus from institutional investors who need to trade large amount of shares within a short time interval. This concern is based on the notion that high frequency traders have the ability to observe the trading intentions of an institutional investor and use their speed advantage to trade ahead of the institutional investor (see for example Zhang, 2010, Cartea & Penalva, 2011). Thus, the debate over high frequency trading can be viewed as a concern that one group of players are in some way victimizing other, technologically less sophisticated parties (Kearns et al., 2010). Hasbrouck and Saar (2011) argue that while the early advocates of electronic equity markets envisioned equal access to all market participants, the structure of today's market place resembles that of floor based markets where access to the floor was purchased or rented in the form of a seat. The co-location services offered to high frequency traders resemble the seats of floor based exchanges, as co-located traders have a significant speed advantage over other market participants (Hasbrouck & Saar, 2011).

Fourth commonly raised concern regarding high frequency trading is the potential systemic risk arising from computerized trading activity. According to Gomber et al. (2011), such risks can result from malfunctioning or rogue algorithms that can drive the market infrastructure to the point where it can no longer cope with the amount of incoming orders. A malfunctioning algorithm might also have the potential to drive the price of a security into an unintended direction and cause severe disturbance in the market. These concerns are highlighted by the diminishing role of traditional market makers as high frequency traders acting as ELPs have taken their role in providing markets with liquidity.

On the other hand, proponents of high frequency trading argue that high frequency trading improves market quality by increasing liquidity and reducing bid-ask spreads (Zhang, 2010). The proponents also argue that high frequency traders improve the price discovery process of markets by using their speed to quickly analyze changes in macroeconomic conditions, company fundamentals or other factors affecting equity valuations. To address the issue about equal access to markets, proponents of high frequency trading argue that guaranteeing equal access to market data in a continuous and fragmented market is physically impossible as geographic dispersion alone produces transmission delays. Garvey and Wu (2009) find that market participants located near New York City experience faster order execution times and lower trading costs compared to market participant situated further away from the exchanges.

The above dimensions in the debate over high frequency trading render it both interesting and important, because high frequency traders have drastically changed the equity trading landscape. While most of the concerns over high frequency trading in the media are about issues concerning predatory activities, most academic studies on the subject examine the effects of high frequency trading on market quality.

1.3. Existing literature at a glance

This section briefly discusses the definition of high frequency trading and covers the findings of the seminal papers in the field. For a more detailed review of the existing literature, see Chapter 3.

Academic studies have discussed formal definitions for algorithmic and high frequency trading, but have not reached a clear, widely accepted definition (Brogaard, 2011b, Gomber et al., 2011). The exact definition will be discussed in more detail in Chapter 2, where the following definition is chosen for this paper: high frequency trading is a subset of algorithmic trading in which: (1) holding periods are extremely short, (2) a massive number of orders are generated and cancelled, (3) the purpose is to make instant profits, and (4) virtually no open position is carried at the end of the day.

Although the academic literature concerning high frequency trading is only developing, there are a number of studies that examine the impact of high frequency trading on market quality. The existing literature shows mixed results on the effects of high frequency trading on market quality. While some studies identify the general improvement in liquidity and reduction in spreads as stemming from the increased share of computerized trading, other studies provide evidence of possible harmful effects under stressful market conditions or point out the possibility of predatory practices which can be exploited by high frequency trading.

One of the earliest studies about high frequency trading is from Zhang (2010). His paper suggests that the increased share of high frequency trading is positively correlated with stock price volatility and that high frequency trading hinders market's ability to incorporate information about firm fundamentals into asset prices. Zhang also finds a stronger effect of the increased volatility for stocks with high institutional holdings, which suggests that high frequency traders are able to take advantage of individual investors who trade in large blocks.

Kirilenko et al. (2010) study how high frequency trading contributed to the "flash crash" in May 2010. The paper examines over 15 000 trading accounts that are classified into different categories with respect to trader type. The results of the study are that high frequency traders did not trigger the crash but their behavior exacerbated market volatility during that day. The authors point out that high frequency traders may create a false signal of ample liquidity with their high levels of trading activity, and because of this, the trading activity of institutional investors may produce a larger than expected price impact. The authors also analyzed the trading patterns of the high frequency traders in their data sample. They find that due to their speed advantage or superior ability to predict price changes, high frequency traders are able to buy right as the prices are about to increase and vice versa.

Jarrow and Protter (2011) also report negative aspects of high frequency trading. Their paper shows that high frequency traders can decrease the efficiency of the markets through increased volatility and asset mispricing. The authors show how high frequency traders can create a trend in market prices that they subsequently exploit to the disadvantage of ordinary traders. The authors point out that the trend is created through a collective but uncoordinated action by the high frequency traders who observe large incoming orders from institutional investors.

Cartea and Penalva (2011) analyze the impact of high frequency trading in equity markets by a model with three types of investors: liquidity traders, market makers and high frequency traders. The authors argue, much like Zhang (2010), that high frequency traders extract surplus from institutional investors by increasing the price impact of trades in proportion to the size of the trade. This effect makes the marketplace a less effective channel through which investors can convert equity into cash and vice versa.

On the other hand, research by Brogaard (2011a) suggests that high frequency trading decreases intraday volatility. The paper also examines how volatility affects high frequency trading by analyzing high frequency trading activity around company news announcements. The paper suggests that volatility generally increases the extent to which high frequency traders supply liquidity, and decreases the amount of liquidity high frequency traders take from the market. Castura et al. (2010) also provide evidence that high frequency trading has made the U.S. markets more liquid and effective. They find a sympathetic relationship between high frequency trading and short-term volatility, liquidity and bid-ask spreads. The authors note that the presence of high frequency trading has benefited all investors by reducing average trading costs in the market.

Cvitanic and Kirilenko (2010) examine the impact of high frequency trading on asset prices. The theoretical model constructed in their paper suggests that the presence of a high frequency trader is likely to change the average transaction price, even in the absence of new information. They also find that in a market with high frequency traders, the distribution of transaction prices has more mass around the center and thinner tails.

Hasbrouck and Saar (2011) study high frequency trading, or “the millisecond environment”, as they call it, using order-level data from NASDAQ. The authors develop a measure of high frequency trading by identifying strategic runs, which are linked order submissions, cancellations and executions that are part of a dynamic trading strategy. These dynamic trading strategies refer to strategies that are conditional on the state of the order book, and thus triggered by events on the micro-market level, such as changes in bid/ask prices. The empirical findings of the paper suggest that high frequency trading improves market quality with respect to liquidity, volatility and bid-ask spreads.

Cont et al. (2008) develop a continuous-time stochastic model to study the dynamics of limit order books. The paper models a limit order book as a continuous-time Markov process that tracks the number of limit orders at each price level of the book. In a Markov process, the next state of the process depends only on the current state, and thus the past and future of the process are independent. In their model, arrival of limit orders, market orders, and cancellations are modeled as Poisson processes where the arrival rate of orders depends on the distance to the bid/ask price. This model is discussed in greater detail in Chapter 3. The authors are able to compute probabilities of events, such as an increase in the mid-price, conditional on the state of the order book. In addition, they estimate parameters for their model using high frequency data from the Tokyo Stock Exchange. Their model can capture short-term dynamics of a limit order book, and can thus be used to create a model for a high frequency trader engaged in statistical arbitrage.

In order to gain deeper understanding of the effects of high frequency trading, academics have started to look at the actual order flow data on a microscopic level instead of aggregate trade data. Studies investigating the economic forces affecting quotes, trades and prices fall under the label *market microstructure* studies. Advances in trading technology during recent years have also increased the quality of data available for academic studies in the field. One could argue that capturing the dynamics of high frequency trading is only possible using high frequency data, and thus, most recent papers apply methods to study the impact of high speed trading by analyzing limit order book data from the markets.

1.4. Motivation for this study

Both regulators and market participants (IOSCO, 2011, SEC, 2010) are calling for more studies about high frequency trading to understand its effects on market efficiency, fairness and integrity of markets, and the stability and resiliency of markets. The existing literature uses a variety of methods to study high frequency trading and its impact on market quality. The results seem to be mixed. On one hand, high frequency trading is shown to make markets more efficient, but on the other, high frequency traders are shown to possess an advantage that allows them to discriminate other market participants.

The existing literature about the role of high frequency trading focuses on the U.S. markets, but it is reasonable to assume that high frequency trading is widespread in most developed nations with efficient capital markets. The lack of studies about high frequency trading outside the U.S. makes it difficult to assess the importance of high frequency trading on a global level. Especially in Europe, where financial markets are deeply integrated, policy makers would benefit from high frequency trading studies using European data.

This study will aim to contribute to the academia by providing detailed information about high frequency trading in NASDAQ OMX Nordic Exchange Helsinki. The information provided by this study can be used by academics to assess the need for further studies about the role of high frequency trading in European equity markets.

1.5. Research questions

The purpose of this study is to estimate the degree of high frequency trading in Helsinki Stock Exchange by using order level data from NASDAQ OMX Nordic Exchange Helsinki. The data allows construction of a limit order book, which is used to compute a number of high frequency trading related metrics, such as the *order flow imbalance*, the hazard rated and the number of orders generated and cancelled. These measures are discussed in more detail in Chapter 4 and Chapter 5.

More precisely, this study aims to answer the following research questions:

I. What is the degree of high frequency trading in NASDAQ OMX Nordic Exchange Helsinki and what are its characteristics with respect to trading strategies?
II. Are there any identifiable dynamics in the order generation and cancellation activities of the identified high frequency traders?
III. Is there evidence of any short-term relationship between high frequency trading order flow and stock price?

Estimating the degree of high frequency trading NASDAQ OMX Nordic Exchange Helsinki serves as an important research objective as regulators in many developed countries are discussing the role of high frequency traders and the need for additional regulation concerning them. Also, identifying the characteristics and the trading strategies of the high frequency traders in NASDAQ OMX Nordic Exchange Helsinki contributes to a broader understanding of high frequency trading and can help to clarify their role in the overall equity market structure.

The findings of this study are useful in assessing the need for further studies about high frequency trading and its impact on securities markets. Further research on the topic will then aid regulators in their challenging task of setting up an efficient regulatory framework for computerized securities trading.

1.6. Empirical study

The empirical study is based on order flow data from NASDAQ OMX Nordic Exchange Helsinki, which contains all (buy and sell) limit orders, market orders, and cancellations for five selected liquid stocks for a one week period in November 2010. The stocks in the data are Nokia Corporation, UMP-Kymmene Corporation, Sampo PLC A, Fortum Corporation and Stora Enso Oyj R. The limit orders, market orders and cancellations are used to construct a representative limit order book for the sample period. A limit order is an order to trade a certain amount of a security at a given price. A limit orders is posted to the electronic trading system where it is recorded in the order book until it is executed against a market order or it is cancelled. A market order is an order to trade a certain amount of a security at the best available price in the limit order book. When a market order arrives, it is matched with the best available price in the order book and a trade occurs. The data used in this study allows observing the state of the limit order book at any given time. The state of the order book gives the number of outstanding buy and sell orders at each possible price. The lowest price for which there is an outstanding sell order is called the ask price and the highest buy price is called the bid price. The data is described in more detail in Chapter 4, where the limit order book construction process is also discussed.

The degree of high frequency trading can be analyzed by looking at the dynamics of the order book. A number of measures are calculated to investigate the high frequency trading environment in NASDAQ OMX Nordic Exchange Helsinki. These include hazard rates for order submissions and cancellations. The hazard rate for submissions and cancellations gives the intensity of submissions and cancellations conditional on the time since any order book event. Also, the speed of response to market effects is calculated from the order book. This metric measures the time it takes for market participants to react to order book events which either increases the bid price or decreases the ask price. The different measures about the degree of high frequency trading are discussed in more detail in Chapter 5.

1.7. Results

The findings of this study suggest that the limit order book in NASDAQ OMX Nordic Exchange Helsinki is dominated by a handful of high frequency traders using sophisticated algorithms and accessing the marketplace with very low latencies. Together the trading accounts identified as high frequency traders capture a majority of the order flow, measured as their ratio of limit orders and cancellations to aggregated market values.

This study also finds that the high frequency traders' order generation dynamic is highly periodic, as measured with message runs. The high periodicity indicates that the high frequency traders react to changes in the order book by simultaneously updating a vast amount of their existing orders. Further, this study finds two discernible dynamics in the high frequency traders' order flow behavior. On one hand their limit order cancellations are followed by new limit order messages within time period of 200ms. On the other hand they often cancel their limit orders rapidly after placing a limit order in the system, which indicates that they constantly update their limit order offering.

The results of this study also indicate that there exists a weak short-term relationship between high frequency trading order flow and stock price change. The results suggests that increased limit order arrival rates for buy orders tend to increase the stock price, and increased limit order arrival rates for sell order to decrease the stock price. The duration of this relationship varies from 150ms to 60ms, depending on the security, and is non-existent for the most liquid share in the sample.

1.8. Structure of the study

The rest of the paper is organized as follows. Chapter 2 provides key definitions and concepts, as well as information about the most common high frequency trading strategies. In Chapter 3, the existing literature is discussed in more detail. Chapter 4 describes the data and methods used in the paper. Then, Chapter 5 identifies high frequency trading accounts from the data. Finally, Chapter 6 discusses the findings of the study and Chapter 7 concludes.

2 Definitions and related concepts

This chapter discusses how prior literature has defined high frequency trading and gives the exact definition used in this study. The purpose of reviewing the definition of high frequency trading is to establish a connection with this study and the previous academic literature, and to make the findings of this study easier to reproduce. In addition, this chapter discusses related concepts and common high frequency trading strategies, which are divided into separate sections. Section 2.4 briefly covers the background behind the rise of high frequency trading.

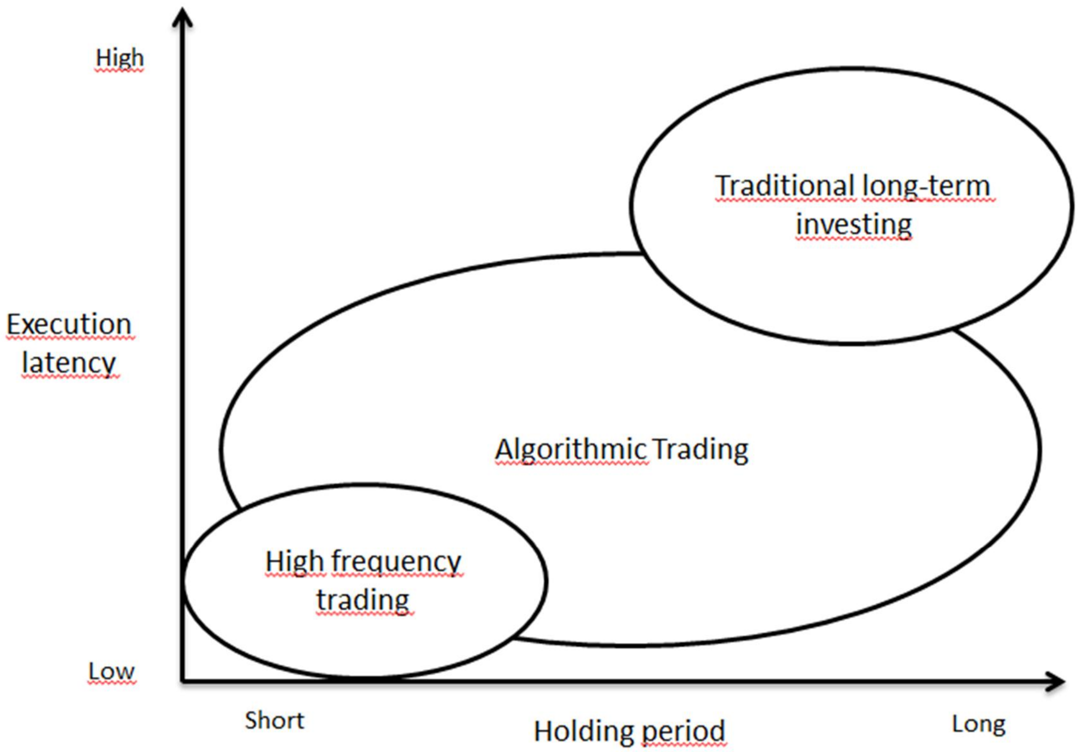
2.1. Formal definition of high frequency trading

In order to assess the importance of high frequency trading and its effect on trading in financial securities, clear definitions of high frequency trading and related concepts are needed. Unfortunately, no clear definition has so far emerged in the academic literature (Brogaard, 2011b, Gomber et al., 2011). The lack of clear definition is partly due to the fact that academic literature about the topic is only starting to develop, and partly because of the rapid development in algorithmic and high frequency trading strategies.

In general, algorithmic trading is viewed as a tool for professional traders to automatically execute a desired trading strategy without the need for human intervention. High frequency trading is often classified as part of algorithmic trading, but all forms or algorithmic trading cannot be classified as high frequency trading (IOSCO, 2011). The definition of high frequency trading is thus best developed by first discussing the definition of algorithmic trading. Hendershott and Riordan (2009) define algorithmic trading as the use of computer algorithms to automatically make trading decisions, submit orders, and manage those orders after submission. Gomber et al. (2011) identify seven common characteristics of algorithmic and high frequency trading: (1) pre-defined trading decisions, (2) use by professional traders, (3) observing market data in real time, (4) automated order submission, (5) automated order management, (6) no human intervention, and (7) use of direct market access. In addition to these common characteristics, the authors also identify a set of characteristics of algorithmic trading which do not hold for high frequency trading. These are: (1) used in agent trading, (2) object to minimize market impact for large orders, (3) goal to achieve a particular benchmark, (4) holding periods from days to months, and (5) object to work an order through time and across markets. Algorithmic trading can thus be thought as a broader set of trading strategies, of which high frequency trading forms one part.

To be more precise, Zhang (2010) identifies high frequency trading as a subset of algorithmic trading that differs with respect to holding periods and trading purposes. Brogaard (2011b) adopts the definition of SEC (Securities and Exchange Commission, 2010), who refers to high frequency trading as “professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis”. Cvitanic and Kirilenko (2010) are more specific and define high frequency trading as trading that employs extremely fast automated programs for generating, routing, canceling, and executing orders in electronic markets. Further, according to their definition, high frequency traders submit and cancel a massive number of orders and execute a large number of trades, trade in and out of positions very quickly, and finish each trading day without a significant open position.

This paper draws on the work by Cvitanic and Kirilenko (2010) by defining high frequency trading as a subset of algorithmic trading where: (1) holding periods are extremely short, (2) a massive number of orders are generated and cancelled, (3) the purpose is to make instant profits, and (4) virtually no open position is carried at the end of the day.



Graph 1: High frequency trading versus algorithmic trading and long-term investing

When discussing the role and impact of high frequency trading, the concept of latency must be discussed in more detail as well. Hasbrouck and Saar (2011) define latency as the time it takes to learn about an event, generate a response, and have the exchange act on the response. This definition of latency can be thought to be composed of three individual parts: (1) the time it takes for the information to reach the trader, (2) the time it takes for the trader's algorithm to analyze the incoming data and generate a response, and (3) the time it takes for the response to reach the exchange and get implemented. The first and third parts of these are heavily influenced by the market operator's infrastructure and possible co-location services they are providing, while the second part is only influenced by the market participants own trading processes.

2.2. Algorithmic trading strategies

This section describes some of the most common algorithmic trading strategies. The development of the strategies is subject to the degree of sophistication in their underlying trading algorithms.

Participation rate algorithms are relatively simple mechanisms that aim to build or liquidate a target position in an instrument by participating in the market up to a given volume. By limiting the rate of participation, these algorithms can be used to liquidate a large position discreetly over a longer period, which is designed to reduce the market impact of the trades. More sophisticated versions of these algorithms can include randomized participation rates, which make it harder for other market participants to detect such strategies (Gomber et al., 2011).

Time weighted average price (TWAP) algorithms divide a large order into pieces which are sent to the markets with pre-determined time intervals. TWAPs can also vary their order sizes and time intervals to avoid detection by other market participants.

Implementation shortfall algorithms try to minimize the market impact of a large order optimizing an execution plan with respect to estimated price movements caused by the execution. The algorithm uses historical data to predict the optimal size and time periods for execution. More sophisticated implementation shortfall algorithms analyze real-time market data to evaluate and adapt their optimal execution plan.

2.3. High frequency trading strategies

Because of the ambiguousness of the definition of high frequency trading, and because the community of market participants using high frequency trading strategies is highly diverse, it is impossible to exhaustively list all possible trading strategies that can benefit from employing high frequency trading. Instead, the following sections discuss some of the best known strategies. The categorization is based on Aldridge (2010) and each category is discussed in its own subsection.

2.3.1. Electronic liquidity provision

Like traditional market makers, electronic liquidity providers post offers on both sides of the market and profit from earning the bid-ask spread. In this strategy, which is referred to as spread capturing, an ELP earns the difference between the price at which market participants can buy securities from the ELP and the price at which they can sell them to the ELP. Unlike traditional market makers, ELPs have no formal market-making obligations, and can thus enter and exit positions very quickly. ELPs can also profit from rebates or reduced transaction fees which are provided by trading venues in order to increase liquidity. The strategies that benefit from the asymmetric pricing schemes are commonly known as Rebate Driven Strategies.

Electronic liquidity providers use mainly limit orders to execute their trading strategy (Aldridge, 2010). As the gain from one individual trade is very small, the strategy requires the trader to constantly move in and out of positions to capture profits. As a result, these strategies operate at very high frequencies and position holding times are extremely short which results to a massive number of orders generated by the trader. Electronic liquidity provision is thus extremely sensitive to a trader’s latency and its ability to handle massive amounts of data.

2.3.2. Market microstructure trading

Market microstructure trading refers to trading strategies that involve the dimension of specifically addressing the intent and future actions of other market participants. These strategies often involve game-theoretic approaches to discover the intentions and information content of another market participant. The goal of market microstructure trading strategies is to identify informed investors and the objectives of their trading operations by employing an algorithm to extract information from the order book. One way of doing this is to monitor the order book for changes in the order aggressiveness, which refers to the percentage of market orders and marketable limit order with respect to total submitted orders. The order aggressiveness can be used to estimate the degree of investors who believe that the price of the security is about to move away from its current price. Vega (2007) shows that better informed market participants trade more aggressively, which implies that order aggressiveness could predict future price changes.

Market microstructure trading strategies also monitor order flow, which can reflect market participants' beliefs about the upcoming direction of the market. Cont et al. (2011) show that over short time intervals, price changes are mainly driven by *order flow imbalance*, which is the imbalance of supply and demand at the best bid and ask prices. A Supporting finding comes from the foreign exchange market, where Love and Payne (2006) find that order flow directly accounts for at least half of all the information transmitted into market prices.

2.3.3. Event trading

Event trading strategies refer to strategies in which high frequency traders trade on the market movements surrounding company news announcements and other information arrivals. The goal of event trading strategies is to identify portfolios that return positive profits over the time window surrounding the specific event. The holding time in these strategies can vary anywhere from a few seconds to several hours and the main driver of profits is the speed of response to the events, which makes the strategy especially suitable for high frequency traders.

The event trading strategies can be used to engage in trading following either expected or unexpected information arrivals. Expected information arrivals constitute of releases of macroeconomic indicator for example. The event trading algorithms compare events to similar historical events and estimate expected price changes in the securities based on historical price behavior surrounding these events.

2.3.4. Statistical arbitrage

In statistical arbitrage strategies, traders profit from short-lived discrepancies between prices of securities. Statistical arbitrage strategies are based on extensive data mining and identification of pervasive statistical relationships between two securities or some variables linked to the securities. For example, the relationship could be between the prices of two different securities, the price of a security and its price in the past, the price of a security and the volatility of another. The idea in statistical arbitrage is that if at any time the relationship deviates from its historical pattern, the relationship will mean-revert to its natural level and a trade should be placed towards that direction.

These strategies are not conducted by high frequency traders alone, but their speed advantage allows them to apply statistical arbitrage strategies to a wider set of relationships and to effectively compete in areas where the strategies are most often used.

2.4. Background for high frequency trading

Gomber et al. (2011) identify four drivers for the emergence of algorithmic trading and high frequency trading: (1) new market access models and (2) fee structures, (3) a dramatic reduction in latency, and (4) an increase in competition and order flow.

The first driver is associated with market access. Similar to the floor-based trading, market access in most electronic markets is only granted to selected members. These members, which are referred to as brokers, are the only ones allowed to conduct trade directly at the marketplace, and are thus in a role of market intermediaries for other investors. This role has been altered by new market access models, Direct Access Model (DMA) and Sponsored Access (SA). In DMA, an investor's orders are forwarded directly to the exchange through the broker's infrastructure and the broker is able to conduct pre-trade risk checks. In SA, an investor who is not a member of the market can access the respective market by routing its orders through its own infrastructure while using a registered member's trading ID. Both DMA and SA allow investors to access the market with significantly lower latencies compared to traditional market access.

Another driver for algorithmic and high frequency trading is the market operators' fee structures that incentivize large order flow and liquidity provision. If the pricing for liquidity providing and liquidity reducing orders differ, it is referred to as asymmetric pricing and is supposed to encourage liquidity provision in the market. In asymmetric pricing, liquidity providing orders are charged a lower fee or even a rebate in some markets, whereas liquidity reducing orders are charged a higher fee. Both special discounts for automatically generated order flow and asymmetric pricing has made high frequency trading strategies more widespread since they are able to use their speed advantage to make profits using discounts and possible rebates.

The use of computerized order driven markets has dramatically reduced the latency, or the time it takes to post a quote to the market and to receive market information. Lower latency reduces the risk an investor faces when posting an order to the market. According to Liu (2009), the risk can be divided into two components: the Free Trading Risk (FTO) and non-execution risk. FTO implies that the value of the bid or ask offer in the system is subject to arrival of public information. The non-execution risk means that the order might not get executed according to the investor's optimal schedule, which creates an opportunity cost. Lower latency allows an investor to react faster to any arrival of public information and to cancel and revise her orders accordingly. Increase in computing power has led to sharp reduction in the average latency as the market system can process orders and execute them faster. Lower latency allows an investor to react to an arrival of public knowledge faster and to cancel or to revise an existing bid or ask quote accordingly. In addition to technological change, co-location services have contributed to the reduction in latencies in the previous decade (Gomber et al., 2011). Co-location services allow the market participants to place their trading machines in physical proximity to the infrastructure of the market operator, which significantly decreases their latency.

Increased competition in the securities market has been driven by regulatory changes. In Europe, the Markets in Financial Instruments Directive (European Commission 2004) fostered competition by harmonizing regulation for investment services across the member states of the European Economic Area. The directive introduced Multilateral Trading Facilities (MTF), financial trading systems which compete with traditional stock exchanges for trading volume. As opposed to traditional exchanges, MTFs do not have a listing process but rather allow for buyers and sellers to trade with securities listed on other exchanges. In order to gain market share, MTFs used aggressive pricing and forced traditional exchanges to revise their pricing schemes as well (Gomber et al., 2011). This fragmentation of the market imposed additional costs for market participants in the form of searching for best prices across different trading venues (Gomber et al., 2011). To tackle these costs, algorithmic trading strategies emerged which automatically optimized trading a large block of shares through different venues.

3 Review of literature

This chapter discusses the existing literature in more detail. Each section presents one paper in the field.

3.1. Menkveld (2011)

A recent paper by Menkveld (2011) links the rise of high frequency trading with increased fragmentation in the equities trading. The author analyzes Chi-X, a multilateral trading facility (MTF) that entered European equity trading in 2007, in its early days. The paper suggests that the presence of a high frequency trader, who operated also in the incumbent marketplace, significantly increased Chi-X's market share and drove down bid-ask spreads. Menkveld focuses on a single high frequency trader on Chi-X and gives interesting details about its operations as a multi-venue market maker. The high frequency trader uses capital to produce liquidity and earns revenue from the bid-ask spread and changes in mid-quotes during the life of non-zero positions.

Menkveld uses a microeconomic perspective and analyzes the profitability of the high frequency trader. His empirical study suggests that the high frequency trader makes a gross profit of 0,88€ per trade, which is a result of a 1,55€ profit from the spread and a position loss of 0,68€. The position loss here refers to the risk of mid-quote movements during market-making, and the author notes that the position loss is consistent across all stocks in the scope of the study. This finding gives support to the proponents of high frequency trading since it indicates that high frequency traders suffer constant positioning losses and thus cannot earn a profit by speculating on the expense of other traders.

The author also reports that the high frequency trader earns roughly five times more from trades of large stocks, as compared to trades of small stocks (with respect to market capitalization). Menkveld suggests this is because trades in large stocks are generally twice the size of those in small stocks. Another interesting finding of the paper is that the high frequency trader does not actively manage cross-security positions to remain market neutral, but instead seems to engage in the market-making on a stock-by-stock basis.

3.2. Zhang (2010)

One of the first academics to study high frequency was Zhang (2010), who investigated the effects of high frequency trading in US capital markets. The definition used in Zhang's paper is line with the one used in this study. In other words, high frequency trading is considered a subset of algorithmic trading strategies, and that high frequency trading differs from other algorithmic trading strategies with respect to holding periods and trading purposes. Zhang focuses on the effects of high frequency trading on stock price volatility and price discovery. The author notes that high frequency traders acting as ELPs can lower volatility by offering liquidity for individual investors and that ELPs generally do not profit from high volatility since they earn the bid-ask spread.

Keeping this in mind, the author identifies three channels through which high frequency traders can increase stock price volatility. First, high frequency traders acting as ELPs can withdraw their supply of liquidity at any time, and thus a high trading volume might not be a reliable indicator of liquidity. Zhang argues that this can create large swings in the prices, since fundamental investors often use trading volume as a proxy for liquidity. Second, high frequency traders can create momentum by placing large amounts of unidirectional orders and thus attract other momentum traders, which then creates prices swings and increases volatility. Finally, high frequency traders can detect large orders from institutional investors and use their speed advantage to trade in the same direction with the institutional investor, increasing (decreasing) the price of her buy (sell) order.

Zhang's empirical study about the effects of high frequency trading on stock price volatility uses a regression model where volatility is regressed by the following factors: high frequency trading, earnings surprise volatility, sales growth volatility, analyst forecast dispersion, market leverage, firm age, share of institutional holdings, inverse of stock price, firm size, book-to-market ratio, and the past 12-month stock return. The results from the regression with respect to the control variables are in line with prior academic studies on determinants of stock price volatility. To move on to the interesting part of the result, Zhang's study suggests that high frequency trading is positively correlated with stock price volatility, and that the correlation is stronger in stocks with high institutional holdings, and stronger in times of high market uncertainty. These results suggest that high frequency traders are able to extract surplus from institutional investors by detecting large orders and using their speed advantage to front-run these orders.

In addition to volatility, Zhang studies the effects of high frequency trading on market's price discovery process. The author notes that the additional liquidity high frequency traders bring to the market makes it easier for institutional investors to change their portfolio allocations to reflect changes in firm fundamentals. To contrast this, Zhang argues that high frequency traders are not interested in firm fundamentals per se, and trade solely on short-term stock returns. He then goes on to examine if the interaction between these two types of investors, institutional investors who care about firm fundamentals and high frequency traders who do not, has long-term effects on price dynamics.

Zhang's empirical study about the effects of high frequency trading on price discovery process uses *analyst earnings revisions* and *earnings surprise* to proxy for firm fundamental news. The author then examines how firm fundamental news affects the stock price returns by regressing the returns with various control variables. The results of the regressions suggest that high frequency trading increases the positive stock price reaction of (positive) earnings news but also increases the subsequent price reversal. This finding suggests that high frequency trading hinders the price discovery process as it pushes prices too far in the direction of earnings news. As a result, stock prices reverse after the initial reaction.

Zhang hypothesizes three channels through which high frequency traders could cause an overreaction in the share price, following firm fundamental news. The author's first hypothesis is that the trading of institutional and high frequency traders is independent, so that the high frequency trader first observes the company news and reacts to it, which moves the share price. Then the institutional investor observes the news and reacts to it, without taking into account the initial reaction of the high frequency trader, which again moves the share price in the same direction. The second hypothesis of Zhang is that high frequency traders interact with institutional investors by front-running their orders after earnings news. If the high frequency trader can successfully front-run the institutional investor, the overall price reaction is stronger than what it would have been without the high frequency trader. The author's third hypothesis for the underlying process in overreaction is that high frequency traders induce other momentum traders to trade in the direction of the earnings news.

3.3. Kirilenko et al. (2010)

Kirilenko et al. (2010) investigate the "flash crash" on May 6th, 2010 and examine the role of high frequency traders during the day of extreme market volatility. On that day, many US stock market indices, index futures, options and exchange traded funds (ETFs) experienced a temporary price drop of over 5 per cent. To investigate the role of different types of market participants in the course of events, the authors classify over 15 000 trading accounts into one of six categories: (1) high frequency traders, (2) intermediaries, (3) fundamental buyers, (4) fundamental sellers, (5) opportunistic traders and (6) noise traders.

The authors classify the trading accounts into six categories with the following criteria. Intermediaries are those traders who engage in market-making strategy, where a large amount of buy and sell orders are generated, and a net inventory is managed so as to keep net positions close to zero. The authors then define as High Frequency Traders those Intermediaries who generate a very large number of orders. Fundamental Traders are traders who accumulate a significant net position by the end of the day, and they are further classified into Fundamental Buyers and Fundamental Sellers, with respect to their accumulated positions. Noise traders are traders who trade a very small number of shares during the day, and the rest of the trading accounts are classified as Opportunistic Traders, who may behave both like Intermediaries and Fundamental Traders.

The authors find that the trading accounts classified as high frequency traders traded almost one third of the total dollar volume of the day. In addition to that, the net positions of the individual high frequency traders fluctuated around zero. The authors comment that this fact alone gives proof that high frequency traders could have done very little to prevent the dip in the prices. It is also worth noting that these two findings are in line with the definition of high frequency trading, as discussed in Chapter 2. The authors also calculated an *aggressiveness ratio*, which gives the ratio of transactions that remove liquidity from the market as a share of a trader’s total transactions. The aggressiveness ratios for High Frequency Traders, Intermediaries, Fundamental Buyers and Fundamental Sellers are 45.68%, 41.62%, 64.09% and 61.13%, respectively. A ratio of less (more) than 50.00% suggests that the trader is a net provider (taker) of liquidity.

The authors examine the trading behavior of high frequency traders during the course of the day. They report that the high frequency traders initially accumulated a (relatively small) long position as the prices started to decline, but liquidated their positions quickly when the decline started to accelerate. The authors employ a second-by-second regression of the net holdings of high frequency traders with respect to share price. The results of their regression suggest that high frequency traders trade in the same direction as the contemporaneous price (with one second interval) and the prices of the last five seconds. In other words, high frequency traders seem to be buying for five seconds if the contemporaneous price is rising, and selling for five seconds if the price is declining. Another interesting finding of their regression is that the High Frequency Traders seem to reverse their direction of trading after 10 seconds, so that they liquidate their net positions between 10 to 20 seconds after the contemporaneous price increase. The authors note that, possibly due to their speed advantage, the High Frequency Traders are able to buy right as the price is about to increase, after which they liquidate their positions.

The authors find that High Frequency Traders did not alter their trading strategy on May 6th, 2010, and that the price decline was initiated by a disproportionally large sell program by Fundamental Traders. High Frequency Traders, together with Intermediaries were providing liquidity to the selling program, but after their net inventories started to accumulate, they started to liquidate their positions, which together with the selling program started to move the prices downwards. The authors note that the high trading amounts of High Frequency Traders may act as a signal of liquidity to Fundamental Traders. This notion was also made by Zhang (2010), as discussed in Section 3.2. Given that the Fundamental Traders observe liquidity incorrectly, they may engage in a buying/selling order that exceeds the actual liquidity in the markets and thus has significant price impact. In this view, the existence of High Frequency Traders can amplify price volatility.

3.4. Jarrow and Protter (2011)

Jarrow and Protter (2011) construct a model of high frequency trading which suggests that high frequency trading may not increase the efficiency of electronic markets. The model allows high frequency traders to create increased volatility and mispricing that they exploit to their advantage. This result is contrary to the belief that high frequency traders act as arbitrageurs who eliminate mispricing and increase the effectiveness of the equity markets.

The authors note that their model allows for a self-induced mispricing because of downward sloping demand curves and differences in speed of transacting across traders. The model assumes that the markets are perfect, e.g. there are no bid/ask spreads and there is unlimited liquidity. Further, the authors model the price process as completely exogenous so that all traders act as price takers believing that their actions do not affect the price. Their model includes two kinds of traders, *ordinary traders and high frequency traders*, with different speeds of transacting.

The high frequency traders, with their speed advantage, can react to price changes which they account to either firm fundamental news or mispricing. The ordinary traders also observe the signal, but can only act upon it after the high frequency traders because of unspecified constraints in their transacting speed. The model assumes a representative high frequency trader, e.g. all high frequency traders act similarly upon seeing a market signal. Thus, they collectively act like a single large trader. And since demand curves are downward sloping, the actions of the collective unit have a market impact. The authors stress the point that an individual high frequency trader still considers itself a price taker and do not take into account the price impact of its own trades.

The model of Jarrow and Protter formally models the process of front-running, where the high frequency trader generates a very large amount of orders to learn the trading strategy of the ordinary investor and then uses its speed advantage to trade ahead of him. The authors note that in their model, there exists a shift of wealth from ordinary traders to high frequency traders, no matter how clever the ordinary trader is. Their model, which includes many simplifying assumptions, gives backing to the opponents of high frequency trading who see it as distorting equality in the market place as high frequency traders are able to extract surplus from other investors.

3.5. Cartea and Penalva (2010)

Cartea and Penalva (2010) analyze high frequency trading by developing a model with three types of traders: (1) *liquidity traders*, (2) *market makers*, and (3) high *frequency traders*. In their model, liquidity traders come to the market to liquidate their positions which are then temporarily held by the market makers for a liquidity premium. The high frequency traders have the ability to process information faster than the other participants, and thus can act as intermediaries between liquidity traders and market makers, deteriorating the terms of trade for the liquidity trader.

The authors provide stylized examples of the trading strategies and profit making opportunities of high frequency traders. These examples are simple, yet backed by the model of Cartea and Penalva (2010), so as to give a realistic and intuitive idea of how high frequency traders might interact with other traders in the equity markets.

Suppose a liquidity trader who wants to liquidate a large block of shares. To minimize price impact, she divides the block into smaller pieces and starts selling them. As the first pieces enter the market operator's system, the high frequency trader learns the liquidity trader's intentions. The high frequency trader then cancels her outstanding buy orders and posts additional sell orders to increase sell pressure, so as to clear the remaining buy orders at the current bid price. After that, the high frequency trader, by using its speed advantage, posts a large amount of buy orders at a lower bid price ahead of the market maker, who also reacts to the situation, albeit much slower. Given that the liquidity trader still continues the selling program, she faces lower prices and unloads the rest of the block to the high frequency trader. After seeing a drop in supply from the liquidity trader, the high frequency trader cancels its remaining buy orders and simultaneously post sell orders with marginally higher price to offload its long position. The market maker reacts to these orders, which are still under the initial market prices so that it too generates profits.

The authors propose a model where equity markets create social values by allowing financing of economic activity and allowing shareholders to convert their holdings into cash quickly at a reasonable cost. In this setting, market makers acts as counterparties to investors with trading needs, and are willing to hold on to securities until another investor enters the market. To compensate for the risks included in market-making, the market makers earns the bid/ask spread. As mentioned earlier, high frequency traders are introduced in the model, and due to their speed advantage, can extract part of the trading surplus between liquidity investors and market makers.

Their model consists of three time periods, $t = 1,2,3$ and two liquidity traders, $L1$ and $L2$. $L1$ wants to sell i assets at period 1, while $L2$ wants to buy i assets at period 2. There are also M intermediaries, or market makers, who accept $L1's$ trade in period 1 and hold on to the asset until $L2's$ trade in period 2. The asset has price risk as public information about period 3 enters market at periods 1 and 2. Thus, the market maker faces risks when holding on to the asset between periods 1 and 2 and market prices will adjust to take that risk into account. The authors include a single monopolistic high frequency trader in the market. They note that high frequency traders can be expected to possess significant monopoly power since entry to the market is limited by high investment costs with respect to co-location services, hardware, and access to algorithms and data.

The high frequency trader is able to generate profits by observing an increase in the supply/demand that arises from the liquidity traders trading needs. In the model, the high frequency trader is able to impose a *haircut* to the price of the security, e.g. the high frequency trader is able to deteriorate the terms of trade of the liquidity trader. For example, if the liquidity trader engages in a large sell operation, the high frequency trader manages to front-run the liquidity trader and reduces the average execution price of the sell operation. Subsequently, the high frequency trader accumulates long positions in the security which it wants to liquidate to end up with zero inventory. According to the paper, the haircut imposed by the high frequency trader is proportional to the size of the trade of the liquidity trader. This result might be driven by the ability of high frequency traders to only discriminate between orders of different sizes, not between different traders.

The model suggests that the introduction of a high frequency trader doubles the number of trades and that the high frequency trader is able to capture 50 per cent of the rebates offered by the market operator, given that rebates are offered. The authors highlight that the additional trade volume generated by the high frequency trader is not driven by fundamentals, but is rather a consequence of tailor made trades that extract surplus from liquidity traders. While high frequency traders are able to extract surplus from liquidity traders, the net wealth effect for market makers is zero. This implies that liquidity traders bear the costs for the change in market structure as they are the ones whose net wealth is reduced by allowing high frequency traders in the model. From a social point of view, the paper suggests that high frequency trading hinders the effectiveness of the market place by deteriorating the terms with which investors and convert their equities into cash (and vice versa)

3.6. Brogaard (2011b)

Brogaard (2011b) examines the role of high frequency trading in the U.S. equity markets by analyzing (1) trading and quote activity of high frequency traders, (2) the drivers behind the trading activity, (3) the profitability of high frequency trading, and (4) its trading characteristics. The paper uses data from both NASDAQ and BATS exchanges with time stamped trades for 120 stocks in 2008, 2009 and partly 2010. The author notes that the exchanges have identified the groups of firms that are classified as high frequency traders, of which there are 26 in NASDAQ and 25 in BATS. It is worth noting that the exact grounds on which the exchanges identified the high frequency traders remain unknown. Also, it is reasonable to assume that the criteria by which the high frequency traders were selected differ between the two exchanges, which could impose limitations to the study.

With respect to trading activity, Brogaard reports that in the sample, high frequency traders are involved in 68.49% of all dollar volume activity in NASDAQ, with a range from 60.44% to 75.85%. The activity is divided between liquidity supply and demand so that the high frequency traders demand liquidity in 42.74% of dollar volume activity and supply it in 41.12%. This result seems to contrast the notion that high frequency traders are mainly suppliers of liquidity and engage in market-making activities. Brogaard notes that the activity of high frequency traders rises in proportion to the market capitalization of the stock in question. This finding seems to hold in all existing studies on high frequency trading, and it raises the question why high frequency traders are active in the most liquid stocks if their contribution to the market is to provide liquidity.

With respect to intra-day changes in trading activity, the paper suggests that high frequency traders are active for most of the trading day, except for the first and last 10-minute periods of the day. Brogaard also analyzes the role of high frequency traders by looking at the fraction of the day the high frequency traders provide the inside bid or offer for a stock. The results suggest that the fraction of the time increases with stock size, which implies that high frequency traders compete harder for the large and liquid stocks. The paper reports that high frequency traders match or beat the best bid and offer quotes 65.04% of the time. This finding suggests, and credits the proponents of high frequency trading, that the existence of high frequency traders reduces bid-ask spreads.

Brogaard studies the short-term determinants of high frequency trading with a linear probability regression. The dependent variables in the regressions are the following choices for a high frequency trader: (1) buy, (2) buy and supply liquidity, (3) buy and demand liquidity, (4) sell, (5) sell and supply liquidity, and (6) sell and demand liquidity. The explanatory variables are (1) the return of the stock in the previous period (10-second), (2) average time-weighted spread, (3) average best bid depth, (4) the number of shares traded, and (5) the order imbalance. The author uses lagged variables as well as contemporaneous values for the regression in order to identify specific trading strategies, such as momentum strategy, price reversal strategy or spread-premium strategy.

The results of Brogaard's regressions suggest that high frequency traders engage in price reversal strategy where past stock returns increase the probability that the high frequency traders sells. The author also finds that the trading activity of high frequency traders is generally momentum enhancing, as high frequency traders are more likely to buy when there exists a buy order imbalance. Brogaard also reports that high frequency traders are able to systematically anticipate and trade ahead of non-high frequency traders, but the results are statistically significant only for buy trades. The author notes that anticipatory ability could be explained by the fact that high frequency traders can algorithmically analyze market events and thus reacts faster than other market participants. Alternatively, the author suggests that the reason could be that high frequency traders can observe order book patterns arising from institutional investors' buy and sell programs.

3.7. Brogaard (2011a)

Brogaard (2011a) analyzes the impact of high frequency trading on volatility by looking at high frequency trading activity around company news announcements. The data sample used in the paper is from 2008-2009, a period which featured elevated levels of volatility. It allows the author to identify if a high frequency trader was involved in a particular trade and whether it supplied or demanded liquidity. Brogaard analyzes the relationship between high frequency trading activity and volatility, and runs a causality test using a Granger test. A Granger test is a statistical test for determining if a time series is useful in predicting another.

The author first looks at the relationship between high frequency trading and volatility, without paying attention to matters of causality. The results of the empirical analysis suggest that high frequency trading activity varies significantly as volatility changes and that the direction of the change depends of the type of high frequency activity. For short time intervals, an increase in volatility increases the supply activity of high frequency traders but decreases their demand activity. For longer time intervals, on the other hand, both supply and demand activity decrease as volatility increases.

After the author has established a relationship between volatility and high frequency trading activity, he continues to explore the causality. He computes the Granger causality test both ways, the hypotheses being that (1) changes in high frequency trading activity Granger cause changes in volatility, and that (2) changes in volatility Granger cause changes in high frequency trading activity. Variable X is said to Granger cause variable Y if (controlling for relevant variables and lagged variables for Y) lagged variables of X improve the prediction of the current value of Y. Brogaard notes that while Granger causality test alone cannot determine whether buying and selling activities of high frequency traders cause volatility, it is a necessary condition for a causal relation between the two variables.

Brogaard uses a two-equation model to compute the Granger test. He controls for implied volatility through VIX-index, the log of market capitalization, market-to-book ratio, dollar volume of trades during the day for a given stock, average quote depth for the inside bid and ask, and average time-weighted dollar bid-ask spread. He reports that the results of the regressions strongly suggest Granger causality in both directions, e.g. that high frequency trading activity influences volatility, and that volatility influences high frequency trading activity. The author notes that while there is a strong causality in general, the null hypothesis for the Granger test cannot be rejected for small stocks and for the longest time intervals (one day). That the influence of high frequency trading on volatility for small stocks is statistically insignificant is very interesting. Intuitively it would seem likely that high frequency trading could amplify price volatility more strongly in the domain of small stocks since they generally exhibit less liquidity, which implies more price impact for trades.

To further examine the causality between high frequency trading and volatility, the author uses a natural experiment to study how changes in high frequency trading activity influence volatility. The natural experiment here is an exogenous shock to high frequency trading activity, the short-sale ban of 799 financial stocks between September 19th and October 9th 2008. The author notes that short-selling is a reasonable proxy for high frequency trading since the correlation between the two is about 22 % in his sample. He continues that since high frequency traders in general want to keep zero net positions, they use short-selling to be able to quickly switch between long and short positions. The author notes that the short-sale ban indirectly prevented some of the high frequency traders from trading in the banned stocks because their trading algorithms were not set up to handle this additional constraint.

The author reports that the results of the natural experiment suggest a negative relationship between high frequency trading activity and intra-day volatility. This is based on the finding that his empirical tests suggest that a reduction in high frequency trading activity, with short-selling as proxy, was connected with an increase in intra-day realized volatility.

3.8. Hasbrouck and Saar (2011)

Hasbrouck and Saar (2011) study the “millisecond environment”, which refers to high frequency trading environment. Their data is from NASDAQ and includes the top 500 companies by market capitalization as of September 2007. The first sample period is from the last quarter of 2007. The authors note that during the sample period, the market was relatively stable and thus the data is intended to reflect a “normal” market environment. In addition, the authors include a second sample, from June 2008, which represents a period of heightened uncertainty.

The authors calculate the intensity of limit order, market order, and cancellation arrivals to be 53,200 messages per stock in 2007. However, they argue that the message intensity is highly periodic, and calculate a *hazard-rate* measure to capture it. The hazard-rate for a stock is the message arrival intensity, conditional on the time elapsed since the last message. The authors report hazard-rates of roughly hundred times the average message intensity for the first milliseconds after the preceding message. They also report that the high hazard-rates dissipate quickly, so that in 2008, the hazard rate drops by 90 percent from its maximum value after first ten milliseconds. The authors argue that steeply declining hazard rates are consistent with clustering, which refers to the finding that trading activity reflects variation in information intensity. For example, changes in analysts’ forecasts occur seldom and cause elevated levels of trading activity as market participants update their view of the company valuation. Notwithstanding, the authors argue that at time horizons of extreme brevity, market participants are only able to react to local market information, e.g. to information about whether someone is interested in buying or selling in the market.

Hasbrouck and Saar also identify local peaks in the hazard rate data occurring at 60,100 and 1000 ms. The authors argue that these peaks arise from algorithms that periodically access the markets.

They also find that the fastest responders to react to changes in the order book have reaction times of 2-3 ms. By carefully looking at the data, the authors report that the periodicity in the millisecond environment is caused by actions of two different kinds of algorithms. To be more specific, they identify algorithms that cycle in clock-time and algorithms that respond to market events. This implies that the two categories of algorithms can be divided into *agency algorithms* and *proprietary algorithms,* where agency algorithms refer to algorithms used by brokers of institutional investors, and proprietary algorithms refer to high frequency traders. The authors argue that most of the activity in the millisecond environment is caused by interaction between automated algorithms. These algorithms are designed to trigger a response from other algorithms or respond to their signals.

To further analyze the millisecond environment, Hasbrouck and Saar develop a measure of *strategic runs*. Strategic runs are linked order submissions, cancellations and executions that are likely to be part of a dynamic strategy. A strategic run always starts with an order submission, and its subsequent cancellation. Then, a possible resubmission of a non-marketable limit order or a subsequent execution in the same direction with the same quantity is linked to the run if they occur within 100 milliseconds. The authors note that even though they allow 100 milliseconds to pass between messages, 49 percent of the durations between messages in the same run are zero ore one milliseconds. They report that roughly 58 percent of cancellations are part of strategic runs for 2007 data, and 53 percent for 2008 data. The length of a strategic run can be measured by the number of messages, and the authors identify runs with length up to 93,244 messages.

Hasbrouck and Saar use the strategic runs as a proxy for high frequency trading and analyze its impact on market quality measures, such as spread, order book depth, and short-term volatility. The authors report that an increase in high frequency trading activity is associated with lower spreads, greater order book depth and lower short-term volatility. The authors note that the magnitude of improvement in the market quality was larger for 2008 data, from which they gather that high frequency trading activity creates a positive externality to markets at the time the markets need it the most. They also report that low-latency activity helps reduce volatility to a greater extent in smaller stocks during 2008, but for 2007 data there is no visible difference between small and large stocks.

3.9. Cont et al. (2008)

Cont et al. (2008) develop a stochastic model for order book dynamics. A stochastic model is a tool for estimating probability distributions of possible outcomes by allowing for random variation in one or more inputs over time. Their model treats an order book as a continuous-time Markov process that tracks the number of limit orders at each price level in the book. A Markov process denotes a stochastic process which satisfies the Markov property, or condition of memorylessnes, which dictates that the next state of the process depends only on the present state. In other words, conditional on the present state of the system, its future and past are independent.

Consider a market for a financial instrument where market participants can post two types of orders, limit orders and market orders. A limit order is an order to trade a certain amount of a security at a given price, while a market order is an order to trade a certain quantity of a security at the best available price in the order book. Limit orders are posted to the electronic trading system, where they are compiled into a limit order book, which tracks the quantities of limit orders at each price level. The lowest price for which there exists a limit sell order is called the ask price and the highest buy price is called the bid price. When a market order arrives in the system, it is matched with the best available limit order and a trade occurs, after which the limit order book is updated accordingly. A limit order is kept in the limit order book until it is matched with a market order or cancelled.

In the model, limit orders are placed on a price grid {1,…,n} representing multiples of a price tick, where the upper boundary *n* is chosen large enough so that it is highly unlikely that orders for the stock in question are priced higher than *n* within the time frame of the analysis. The state of the order book is tracked by a continuous-time process $X(t) \equiv (X_1(t),\ldots,X_n(t))_{t\geq 0}$ where $X_p(t)$ is the number of outstanding limit orders at price p ,$1 \leq p \leq n$. If $X_p(t) < 0$, then there are $-X_p(t)$ bid orders at price p. If $X_p(t) > 0$, then there are $X_p(t)$ ask orders at price p.

The ask price $p_A(t)$is defined as

$$p_A(t) = \inf\{p = 1,\ldots,n, X_p(t) > 0\}.$$

Similarly, the bid price $p_B(t)$is defined as

$$p_B(t) = \sup\{p = 1,\ldots,n, X_p(t) < 0\}.$$

The mid-price $p_M(t)$ and the bid-ask spread $p_S(t)$ are defined by

$$p_M(t) = \frac{p_B(t) + p_A(t)}{2} \text{ and } p_S(t) = p_A(t) - p_B(t)$$

The number of outstanding bid orders at a distance i from the ask is defined as

$$Q_i^B(t) = X_{p_A(t)-i}(t) \quad , \text{ where } 0 < i < p_A(t).$$

Similarly, the number of outstanding ask orders at a distance i from the bid is defined as

$$Q_i^A(t) = X_{p_B(t)+i}(t) \quad , \text{ where } 0 < i < n - p_B(t).$$

The dynamics of the order book are driven by the incoming flow of limit orders, market orders and cancellations at each price level. When one of these events occur, one of the following must hold true:

- a limit buy order at price level $p < p_A(t)$ increases the quantity at level p
- a limit sell order at price level $p > p_B(t)$ increases the quantity at level p
- a market buy order decreases the quantity at the ask price
- a market sell order decreases the quantity at the bid price
- a cancellation of an outstanding limit buy order at price level $p < p_A(t)$ decreases the quantity at level p
- a cancellation of an outstanding limit sell order at price level $p > p_B(t)$ decreases the quantity at level p

Bouchaud et al. (2002) study the statistical properties of limit order books and suggest that the distribution of incoming limit orders at the bid (or ask) follows a Gamma distribution. The authors report that the price at which new limit orders are placed is broadly distributed around the current bid/ask and that the average order book has a maximum away from the current bid/ask, and a tail reflecting the statistics of the incoming orders.

Motivated by this finding, the model in this paper used a stochastic model where the above events are modeled using independent Poisson processes. A Poisson process is a stochastic process in which events occur continuously and independently of one other. The probability distribution of the waiting time until the next occurrence in the Poisson process is an exponential distribution. More precisely, the model assumes that

- limit buy (and sell) orders arrive at a distance of i ticks from the best quote at independent exponential times with rate $\lambda(i)$
- market buy (and sell) orders arrive at independent exponential rate μ
- Cancellations of limit orders at a distance of i ticks from the best quote occur at a rate proportional to the number of outstanding orders. If the number of outstanding orders at that level is x, then the cancellation rate is $\theta(i)x$

Order arrival rates are modeled to depend on the distance to the bid/ask so that most orders are being placed close to the current best price. Based on the finding of Bouchaud et al. (2002), the rate is modeled as a power law

$$\lambda(i) = \frac{k}{i^a}.$$

Given the above assumptions, X is a continuous-time Markov process with state space $\mathbb{Z}_n$ and the following transition rates:

- x⟶ x^{p-1} with rate $\lambda(p_A(t) - p)$ for $p < p_A(t)$
- x⟶ x^{p+1} with rate $\lambda\big(p - p_B(t)\big)$ for $p > p_B(t)$
- x⟶ $x^{p_B(t)+1}$ with rate μ
- x⟶ $x^{p_A(t)-1}$ with rate μ
- x⟶ x^{p-1} with rate $\theta(p_A(t) - p)|x_p|$ for $p < p_A(t)$
- x⟶ x^{p+1} with rate $\theta\big(p - p_B(t)\big)|x_p|$ for $p > p_B(t)$

The limit order and cancellation arrival rates $\lambda(i)$ and $\theta(i)x$ are used in this study to examine the dynamics of the order generation and cancellation activity of high frequency traders.

4 Data and methods

This chapter describes the data used in this study and the market place from which the data are acquired. This chapter also explains how a limit order book is constructed from raw limit order data. In addition, this chapter uses a number of measures to identify high frequency traders from the data in order to assess their role in NASDAQ OMX Nordic Exchange Helsinki. The measures are linked to the formal definition given in Section 2.1 to clear any potential confusion about findings of this study with respect to their tractability. As discussed in Chapter 3, many previous studies on the effects of high frequency trading use data where high frequency traders are flagged by the data provider, which leave the authors little room to discuss the actual conecpts of high frequency trading.

The data used in this study is order level data from NASDAQ OMX Nordic Exchange Helsinki. It includes all limit orders, cancellations and market orders for five liquid stocks for the period of 22nd – 26th November 2010. The stocks in the data are Nokia Corporation, UMP-Kymmene Corporation, Sampo PLC A, Fortum Corporation and Stora Enso Oyj R. Previous literature has identified that high frequency traders are most active in large and liquid stocks, which suggests limitations to this study as the data is not a representative sample of stocks in NASDAQ OMX Nordic Exchange Helsinki. Instead, the results of this study can be interpreted as an upper limit for high frequency trading in the market place.

4.1. Overview of NASDAQ OMX Nordic Exchange Helsinki

NASDAQ OMX Nordic Exchange Helsinki, commonly referred to as Helsinki Stock exchange, is the primary equity market place in Finland. The stock exchange, which was first established in 1912, has operated under several different owners. The exchange merged with its Swedish counterpart to form OMX AB in 2003, which was subsequently acquired by NASDAQ in February 2008. In addition to Helsinki, NASDAQ OMX Nordic Exchange operates exchanges in Stockholm, Oslo, Copenhagen, Reykjavik, Tallinn, Riga and Vilnus.

Trading volume in NASDAQ OMX Nordic Exchange Helsinki has increased in recent years due to increased activity in algorithmic and high frequency trading, and the average number of trades in 2011 was 85 259 trades per day, an increase of nearly 40 per cent from the previous year. While the number of trades has increased dramatically, the average size of a trade has been declining. The average size of a trade was 6 589 € in 2011, which was over 25 per cent lower than in 2010. Both of these developments are what one could expect to be a result from increased algorithmic, and especially, high frequency trading.

The average daily Euro volume for the 131 listed stocks in the exchange was 547 million Euros for 2011, which was roughly one percent less than in 2010. The five most traded stocks in 2011 were the same as in 2010; Nokia, UPM-Kymmene, Fortum, Stora Enso, and Sampo. Data from these stocks are also used in this study. The stock exchange currently conducts trading with 65 member institutions who have access to the trading platform. The member institutions can provide their access to third party traders, so the actual number of active trading institutions can be substantially larger.

4.2. Limit order data and order book mechanics

This section describes the components of the limit order data and the basic underlying mechanisms behind electronic order driven equity markets.

Orders are messages sent to the market operator’s system that specify a security the trader wants to trade, whether he wants to buy or sell, how much he wants to trade, and with what price. Orders are the fundamental building blocks of electronic markets where the orders are stored in a limit order book and arranged into trades by price-time priority. The prices with which buy and sell orders arrive are called bid and ask prices, and the best standing bid and ask prices in the order book are referred to as inside prices, market bid and market ask, market quotations, or simply just bid and ask. The difference between the best bid and ask prices is called the bid-ask spread, which is considered one of the fundamental indicators of market quality. Small bid-ask spreads indicate that the price with which you can buy a share is close to the price at which you can sell one. Sometimes market participants want to refer to the current market price with one number, without differentiating between buying and selling. To capture this, the *midpirce* gives the arithmetic mean of the market bid and ask prices.

Generally, there are two types of orders with respect to the price the trader is willing to accept. A limit order is an order to buy or sell a stock at a specific price or better. A buy limit order can only be executed at the limit price or lower, and a sell limit order can be executed at the limit price or higher. These orders do not guarantee execution but are stored in the order book as standing orders if not executed immediately upon arrival. A market order on the other hand is an order to buy or sell a stock at the best available price. Market orders are executed immediately against standing orders in the order book. The price at which a market order is executed is not guaranteed but depends on the current state of the order book.

An order supplies liquidity to the order book if it is recorded as a standing order in the order book and gives other traders and opportunity to trade. Conversely, an order demands liquidity if it is immediately matched with a standing order in the order book and thus removes this order from the order book. All market orders demand liquidity since they are immediately executed against a standing limit order in the order book, but limit orders can supply or demand liquidity, depending on the price at which they are submitted. A limit order which is executed immediately is called a marketable limit order. Since the data used in this thesis does not allow classifying between market orders and marketable limit orders, they are both considered market orders.

When a limit order arrives to the market system, it is recorded as a standing order in the order book and stays there until one of the following events occur: (1) the standing order is executed against an incoming market order or marketable limit order, (2) the order is canceled, or (3) the order reaches its maximum time of validity. Cancellation of a limit order can occur either for the whole outstanding amount or for a part of the amount. If an order is cancelled partially, the remaining part of the order stays in the order book with the same order information. In modern equities markets with high frequency traders, most orders are cancelled before they are executed or before they reach their maximum duration. In markets where high frequency traders participate actively, the average duration of an order can be extremely short since the high frequency traders are able to update their orders in a fraction of a second.

4.2.1. Limit order data

Table 1 gives an example of the limit order data. For any given limit order that enters the system, the data gives the name of the security, the date and timestamp. The timestamp value of *mstime* is given as nanoseconds after midnight. The variables *ordersequence* and *mykey* are reference numbers that are used to track orders in the order book. *Side* tells if the order is a limit buy or limit sell order, *quantity* gives the number of shares, and *price* is the price in one hundredth of a Euro cent. *Userid* (information hidden in the table due to data confidentiality) gives the trading account that generated the limit order.

name_long_cur	refdate	ordersequence	mykey	mstime	side	userid	quantity	price
Nokia Corporation	25NOV2010	87435	169656	32402189000000	B	x	500	72150
Nokia Corporation	25NOV2010	87437	169663	32402215000000	B	x	800	72100
UPM-Kymmene Corporation	25NOV2010	87450	169710	32402287000000	B	x	179	117500
UPM-Kymmene Corporation	25NOV2010	87589	169956	32402555000000	B	x	400	117500
Sampo Plc A	25NOV2010	87702	170160	32402767000000	S	x	1000	194400
Nokia Corporation	25NOV2010	87730	170234	32402853000000	S	x	1000	72600
Fortum Corporation	25NOV2010	87896	170568	32403211000000	S	x	100	214700
Fortum Corporation	25NOV2010	87897	170569	32403211000000	B	x	100	173800
Nokia Corporation	25NOV2010	87990	170781	32403396000000	B	x	5000	72300

Table 1: Example of the limit order data

4.2.2. Cancellation and execution data

Table 2 gives an example of the cancellation data. The variables of the table contain information similar to those of limit orders. Any limit order in the order book can be canceled any time by the market participant who inserted the order. The reference numbers *ordersequence* and *mykey* are used to match a cancellation with its respective limit order to track changes in the order book. The matching allows computation of many interesting variables, such as the time the order stayed in the order book and the side and price of the initial limit order, which are not revealed by the cancellation data alone.

name_long_cur	refdate	ordersequence	mykey	mstime	quantity	userid
Sampo Plc A	25NOV2010	579120	1347041	33440000000000	331	x
Fortum Corporation	24NOV2010	579128	1264820	32950000000000	3733	x
Nokia Corporation	25NOV2010	579139	1250766	33360000000000	2787	x
Nokia Corporation	24NOV2010	579184	1246176	32930000000000	492	x
UPM-Kymmene Corporation	22NOV2010	579218	1442353	33360000000000	5610	x
UPM-Kymmene Corporation	22NOV2010	579220	1389183	33310000000000	5041	x
Nokia Corporation	22NOV2010	579223	1272534	33220000000000	3599	x
Fortum Corporation	24NOV2010	579249	1272263	32960000000000	500	x
UPM-Kymmene Corporation	25NOV2010	579272	1770437	33760000000000	1267	x

Table 2: Example of the cancellation data

In addition to limit order and cancellation data, the data used in the study consists of information about the executions that took place during the sample period. *Table 3* gives an example of the execution data, which contains information about each individual execution in the same manner as the data of limit orders and cancellations. In a similar fashion to cancellations, the reference variables *ordersequence* and *mykey* allow matching the executions with their respective limit orders.

name_long_cur	*refdate*	*ordersequence*	*mstime*	*mykey*	*quantity*	*userid*	*price*
Nokia Corporation	*26NOV2010*	*92502*	*32410599000000*	*213744*	*1257*	*x*	*72800*
Sampo Plc A	*25NOV2010*	*92609*	*32433217000000*	*223784*	*180*	*x*	*194800*
Stora Enso Oyj R	*25NOV2010*	*92612*	*32406542000000*	*181496*	*1700*	*x*	*68000*
Fortum Corporation	*26NOV2010*	*92799*	*32401328000000*	*182294*	*736*	*x*	*211600*
Fortum Corporation	*26NOV2010*	*92799*	*32401328000000*	*182291*	*100*	*x*	*211600*
Fortum Corporation	*26NOV2010*	*92799*	*32401328000000*	*182297*	*70*	*x*	*211600*
Fortum Corporation	*26NOV2010*	*92799*	*32401328000000*	*182285*	*100*	*x*	*211600*
Fortum Corporation	*26NOV2010*	*92799*	*32401328000000*	*182288*	*55*	*x*	*211600*
Sampo Plc A	*26NOV2010*	*93059*	*32401584000000*	*182832*	*2308*	*x*	*194900*

Table 3: Example of the execution data

Table 4 lists the average daily number of limit orders, cancellations and executions in each security as a reference of their trading activity. The number of cancellations may exceed the number of inserted limit orders due to partial cancellations.

Symbol	***Name***	***Limit orders***	***Cancellations***	***Executions***
24271	*Fortum Corporation*	*19 148*	*18 831*	*6 414*
24311	*Nokia Corporation*	*198 971*	*279 244*	*19 197*
24346	*Sampo Plc A*	*36 251*	*39 048*	*5 769*
24360	*Stora Enso Oyj R*	*165 099*	*245 734*	*9 262*
24386	*UPM-Kymmene Corporation*	*37 397*	*41 850*	*5 688*

Table 4: Average daily limit orders, cancellations and executions

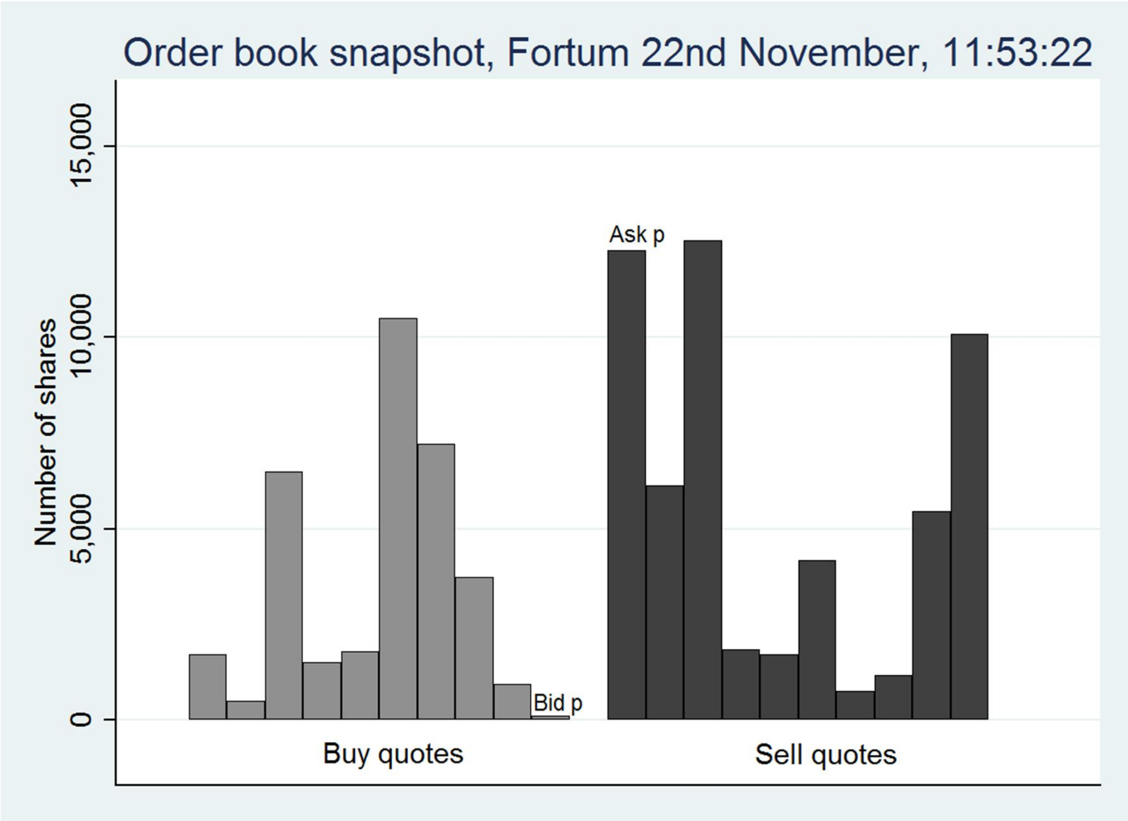
4.3. Order book compilation

This section describes the methods used to compile a representative limit order book from the order flow data.

First, cancellations are matched with their respective limit orders within each trading day and security. This allows observing in which domain, with respect to buy and sell sides, a cancellation occurs. Also, the pairing allows comparing the time labels of the cancellation and its respective order, which gives the exact time the order stayed in the order book. Second, executions are matched with limit orders to identify and label market sell orders from market buy orders. Third, tables of limit orders, cancellations and market orders are merged and sorted on the basis of timestamp to construct the order book in a chronological manner. Observations are analyzed individually and in each row of the merged table, one of the following can happen:

- An incoming buy limit order I_p^B increases the bid quote depth at price p.
- An incoming sell limit order I_p^S increases the ask quote depth at price p.
- An incoming buy order cancellation C_p^B decreases the bid quote depth at price p.
- An incoming sell order cancellation C_p^S decreases the ask quote depth at price p.
- An incoming market buy order M^B decreases the ask quote depth at ask price p_{ASK}
- An incoming market sell order M^S decreases the bid quote depth at bid price p_{BID}

After an observation is classified to the above states, the variables p_{ASK}, p_{BID} and p_{MID} are updated accordingly. This process is done for each observation in the data, and it captures the underlying dynamics of the order book.



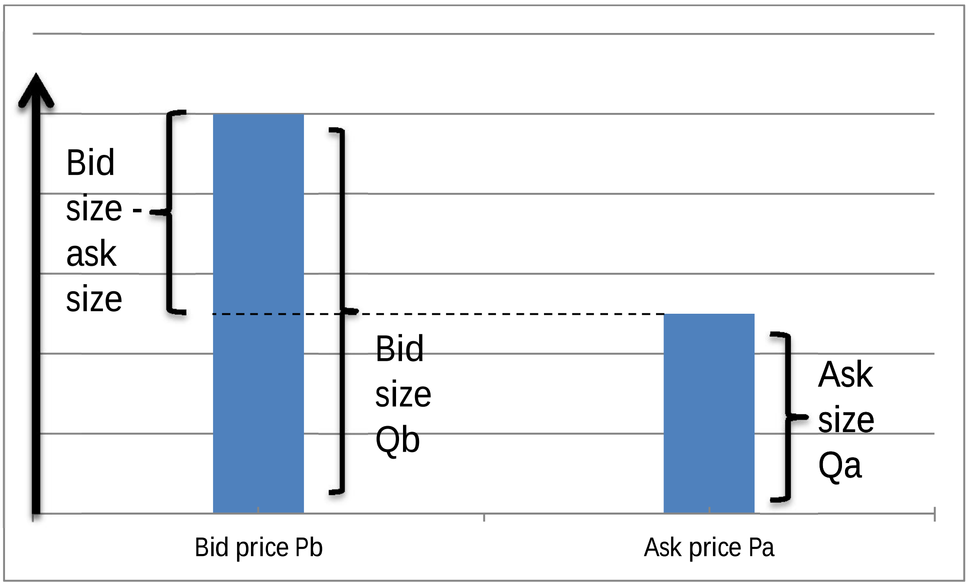
Graph 2: Order book snapshot, Fortum 22nd November 11:53:22

Graph 2 illustrates the limit order book by giving a snapshot of the order book of Fortum PLC at 11:53:22 November 22nd. The graph plots buy and sell quotes at 10 best prices, respectively. In this particular example, the pressure seems to be on the sell side as the quote depth at the best sell prices clearly outnumbers the quote depth at the best buy prices. In fact, looking forward in the data reveals that the *mid-price* is about to decrease after a market sell order removes the existing quote depth at the bid price.

4.4. Order flow imbalance

This section discusses the concept of *order flow imbalance* and explains how it is calculated in this study. Cont et al. (2011) argue that the price dynamics of order book events – limit orders, market orders and cancellations- can be modeled through a single variable, *order flow imbalance* (OFI). The order flow imbalance represents the net order flow in a given security, and tracks changes in the bid and ask quote depths. The variable treats a market sell order and a buy order cancellation (occurring at bid price) as identical events since both reduce the bid quote depth. The authors report that the order flow imbalance explains changes in mid-price in the short-term for a large sample of stocks. The authors dub the slope of the reaction as the *price impact coefficient*, which they show to be inversely proportional to the order book depth. This implies that an incoming order has stronger price impact when the order book depth is low, which seems intuitive given that low order book depth implies less liquidity.

The authors calculate the order flow imbalance by looking at limit orders sitting at the inside prices, e.g. the best bid and ask prices. The construction consists of the bid price P^B, the size of the bid queue q^B, the ask price P^S, and the size of the ask queue q^S. The bid price and the size of the bid queue represent the demand for the security, while the ask price and the size of the ask queue represent the supply.



Graph 3: Illustration of order flow imbalance

The order flow imbalance measure of Cont et al. (2011) looks at the best bid and ask prices, and thus every incoming order either increases or decreases the demand, or then increases or decreases the supply. The authors calculate the contribution of every individual event to the supply and demand of the security, and then define the order flow imbalance as:

$$OFI_k = \sum_{n=N(t_{k-1})+1}^{N(t_k)} e_n$$

where $N(t_{k-1}) + 1$ and $N(t_k)$ are the index of the first and the last event in the interval $[t_{k-1}, t_k,$ and e_n is the contribution of message n to the order flow imbalance.

The order flow imbalance measure used in this study follows the construction of Cont et al. (2011) but expands the scope of the measure by looking beyond the best bid and ask prices. This is motivated by the distribution of orders in a limit order book. The distribution is shown to have a peak away from the best bid/ask and a long tail (Cvitanic & Kirilenko, 2010, Potter & Bouchaud, 2002). In other words, a major share of the incoming orders arrive at prices away from the best bid/ask. The same property is shown to apply in this study as well.

The distribution of incoming limit orders can be explained with asymmetric investor patience. Zovko and Farmer (2002) argue that choosing a relative price (with respect to the current best bid/ask) of a limit order is a strategic decision with a tradeoff between patience and profit. They continue that an impatient investor will submit a limit order at or above (below) the best bid (ask) to secure a transaction. An investor with intermediate patience will submit an order somewhat away from the best bid/ask. This will not result in an immediate transaction, but the order has a high priority if the mid-price changes so that the order becomes marketable. Finally, the authors argue, that a very patient investor will submit an order with a price far away from the current bid/ask, which will potentially lead to a transaction with a very favorable price (compared to the price at the time the order was placed). Thus, Zovko and Farmer theorize that the wide distribution of limit orders imply, among other things, differences in investor patience.

It is reasonable to assume that high frequency traders place a significant share of their orders away from the best bid/ask price. Therefore, expanding the order flow imbalance variable to measure quote sizes for a range of prices near the best bid/ask produces a better tool for measuring changes in supply and demand.

The order flow measure is constructed as follows:

- $q_{i,n}^{S}$ is the contribution of observation n to the size of the ask queue at price i away from the ask price
- $q_{i,n}^{B}$ is the contribution of observation n to the size of the bid queue at price i away from the bid price
- $Q_{i,n}^{S} = Q_{i,n-1}^{S} + q_{i,n}^{S}$ is the cumulative size of the ask queue at price i away from the ask price
- $Q_{i,n}^{B} = Q_{i,n-1}^{B} + q_{i,n}^{B}$ is the cumulative size of the bid queue at price i away from the bid price

- $Q^S_{n,R} = \frac{\sum_{i=0}^{R} Q^S_{i,n} w_i}{\sum_{i=0}^{R} w_i}$ is the w_i weighted mean of the ask queue sizes at prices $i = [0,1,2 \ldots R]$ away from the best ask price at observation n, where $w_i = \left(\frac{4}{5}\right)^i$
- $Q^B_{n,R} = \frac{\sum_{i=0}^{R} Q^B_{i,n} w_i}{\sum_{i=0}^{R} w_i}$ is the w_i weighted mean of the bid queue sizes at prices $i = [0,1,2 \ldots R]$ away from the best bid price at observation n, where $w_i = \left(\frac{4}{5}\right)^i$

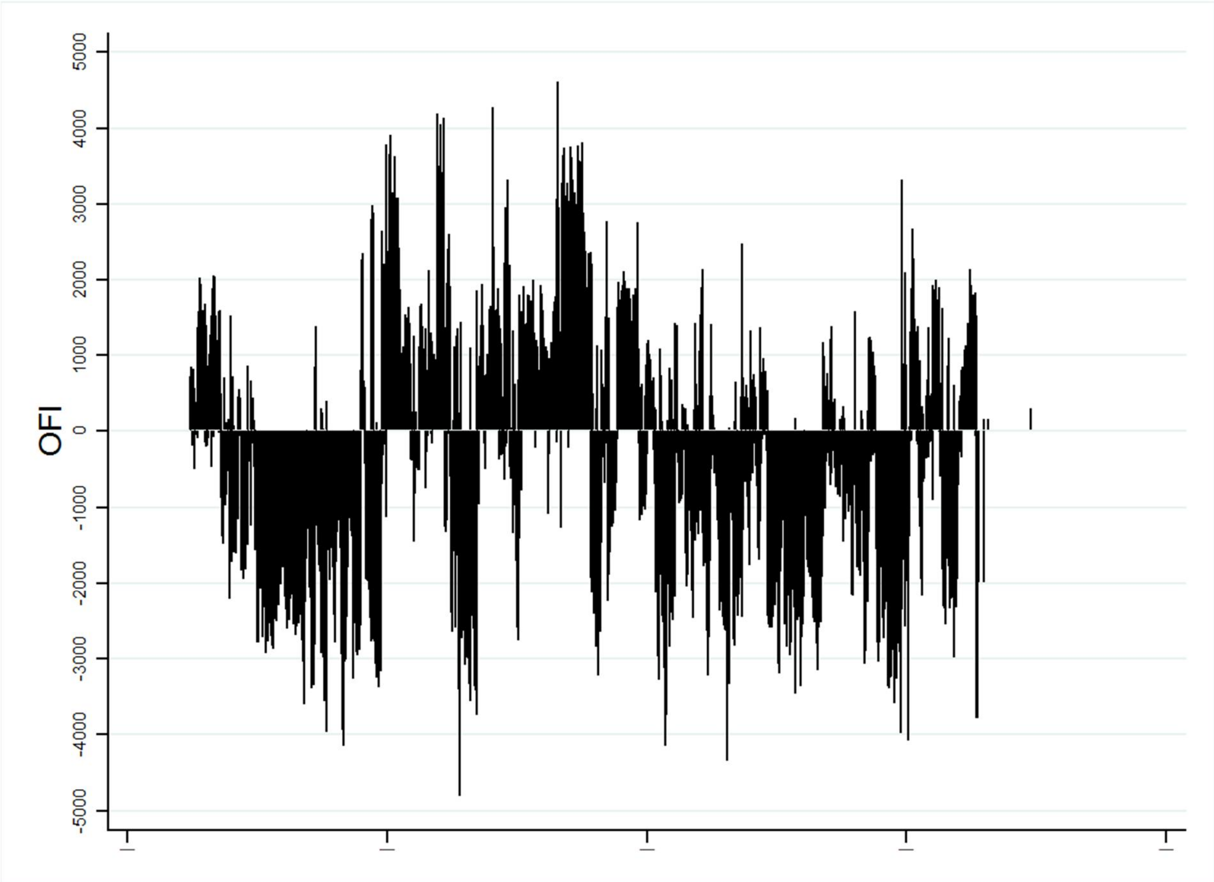
The contributions of limit orders, market orders and cancellations to the variables $q^S_{i,n}$ and $q^B_{i,n}$ follow the same logic as in Section 4.2.

Finally, the *order flow imbalance* is calculated as:

$$OFI_{n,R} = Q^B_{n,R} - Q^S_{n,R}$$

Note that if $R = 0$ the order book imbalance metric reduces to that used in Cont et al. (2011) where only the queue sizes of the inner prices are examined.

Graph 4 illustrates the order book imbalance for Fortum on November 22nd. The *order flow imbalance* variable is plotted on the vertical axis and the variable *mstime* on the horizontal axis. Negative OFI values represent situations where $Q^S_{n,R} > Q^B_{n,R}$, which means that the weighted mean of the sell queues exceed the weighted mean of the bid queues. In this example, $R = 4$, which means that the OFI takes into account five best prices for both bid and ask queues.



Graph 4: Order flow imbalance for Fortum, NOV22. R=4

5 Identifying high frequency trading accounts

This section describes how high frequency trading accounts are identified from the data. The measures used to identify high frequency trading are linked to the definition of high frequency trading, which was discussed in Section 2.1. The exact definition of high frequency trading is restated for the sake of convenience. High frequency trading is defined as a subset of algorithmic trading where: (1) holding periods are extremely short, (2) a massive number of orders are generated and cancelled, (3) the purpose is to make instant profits, and (4) virtually no open position is carried at the end of the day.

The data classifies trading accounts into algorithmic, routing accounts and personal accounts. From this classification, algorithmic and routing accounts stand as potential high frequency trading accounts. The following measures can be calculated in order to identify high frequency accounts:

a) A trading account's average duration of non-zero net position can be used as a proxy for (1) and (3)
b) A trading account's share of orders with respect to total daily limit orders can be used as a proxy for (2)
c) Also, a trading account's ratio of cancellations to limit orders posted by the account can be used as a proxy for (2)
d) A trading account's average daily accumulated net position can be used as a proxy for (4)
e) A trading account's response delay to order book events can be measured with hazard rates. The response delay can be used to estimate the latency of the trading account.

Because the data used in this study does not allow the identification of trading accounts responsible for executions, measures a) and d) are only discussed in Sections 5.1 and 5.2, respectively. Measures b) and c) are computed in Section 5.3, and measure e) is computed in Section 5.5.

5.1. Average duration of non-zero positions

As stated earlier, limitations in the data withhold this study from calculating the average duration of non-zero positions, which could be used as a proxy for a trading account's average holding period. While the actual calculations cannot be made, the general process of calculating the average duration of non-zero positions is discussed in this section. Although the average duration of non-zero positions can be calculated in a number of ways, this study chooses a simple method that catches the underlying idea behind the measure.

Suppose a trading account participates in K trades during a trading day. Suppose further that:

$K = T_i^B + T_i^S$, where T_i^B denotes the timestamp value of a buy trade and T_i^S for a sell trade, and i is the number of the trade.

Then, the average duration of non-zero positions can be calculated as the average time passed since the last trade in the opposing direction that matches or exceeds the size of the newest trade.

5.2. Accumulated net positions

A ratio of the absolute value of accumulated net position and total trading volume can be calculated to capture the net position accumulation behavior of a trading account. High frequency trading accounts are expected to exhibit low ratios, and other trading accounts are expected to exhibit either high or low ratios.

Accumulated net position can be calculated as $NETPOS_{ID} = \sum_{i=1}^{n} Q_i^B - \sum_{j=1}^{n} Q_j^S$,

where Q_i^B denotes quantity of shares bought in transaction i, and Q_j^S denotes quantity of shares sold in transaction j.

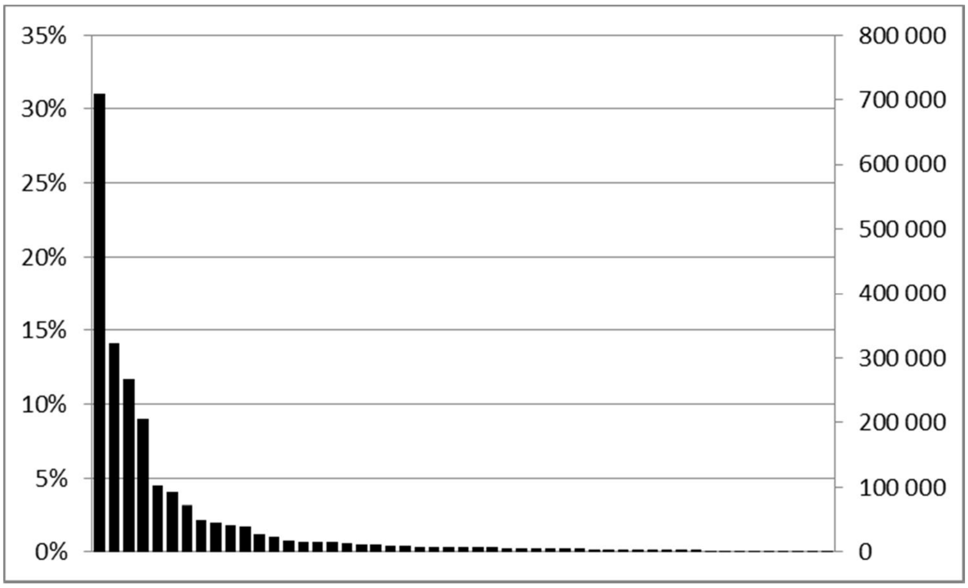
Total trading volume is $TOTVOL_{ID} = \sum_{i=1}^{n} Q_i^B + \sum_{j=1}^{m} Q_j^S$

And the ratio of absolute accumulated net position and total trading volume is

$$\mathrm{NETPOSRATIO}_{ID} = \frac{|NETPOS_{ID}|}{TOTVOL_{ID}}$$

5.3. Number of orders and cancellations

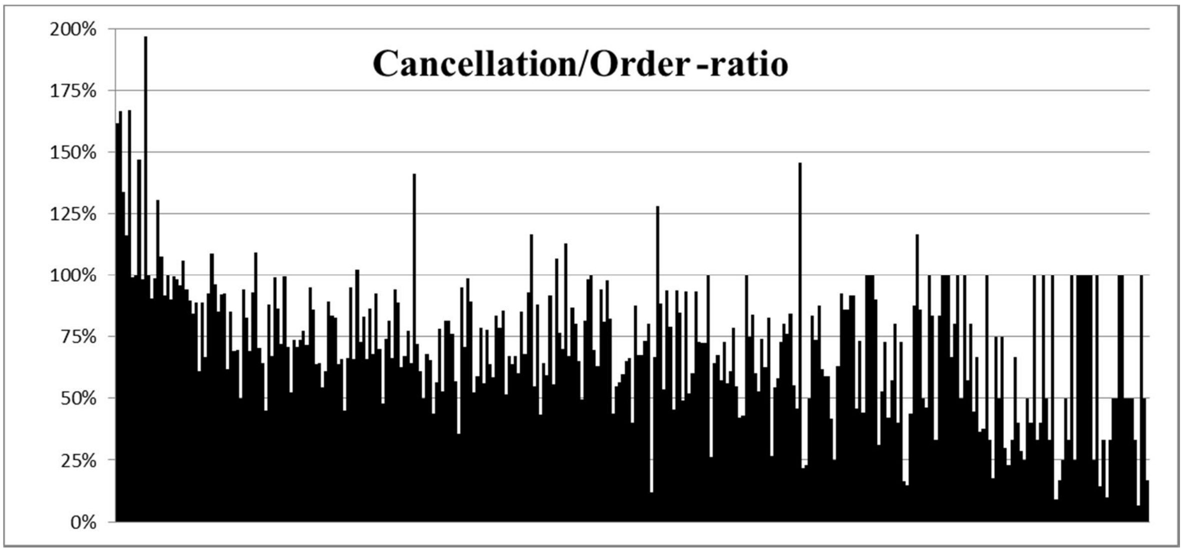
As mentioned in Section 2.1, where the definition of high frequency trading is given, high frequency traders generate and cancel a large number of orders. Therefore, analyzing the number of limit orders generated and cancelled is a viable way to identify potential high frequency traders from the data.



Graph 5: Share of orders by trading ID for the entire data. 50 most active accounts

Graph 5 plots the total numbers of orders posted by 50 most active trading IDs for the whole data sample. The active trading accounts are sorted by their combined number of limit orders for the sample period. The data indicates that there exists one dominating player who posted over 700 000 orders in the sample, which represents over 30 percent of total orders posted by all market participants. There are also three other trading IDs who posted over 5 percent of total orders, as well as nine other traders who posted over 1 percent of orders. The average amount of orders posted by a trading account is 6 398 orders for the sample period, while the median amount is only 48 orders. The large difference in the median and average amounts is caused by the handful of extremely active trading accounts.

In addition to the number of orders generated, it is useful to assess how many of these orders are cancelled. The *cancellation/order –ratio* gives the share of cancellations to posted limit orders. Note that a cancellation can occur for a fraction of the outstanding order amount and thus need not cancel the whole outstanding order. This allows multiple cancellations per posted limit order and hence also cancellation/order –ratios of over 1.



Graph 6: Cancellation/Order ratios for all trading accounts in the data

Graph 6 plots the cancellation/order –ratios for all trading accounts in the data. The accounts are sorted based on their limit order activity so that the leftmost account is the most active and the rightmost the least active. As in the previous graph, the activity of a trading account refers to its amount of combined limit orders for the whole sample data. The cancellation/order –ratios are more uniformly distributed than the posted limit orders but two noteworthy patterns can be seen in the data. First, the most active trading IDs seem to exhibit significantly higher ratios than the other participants and their ratios are generally close or over 1, which implies that most of their limit orders are cancelled. Second, many of the least active trading IDs exhibit ratios of 1, which is caused by their small trading activity (in the domain of under 5 orders for the whole period).

5.4. Hazard rates

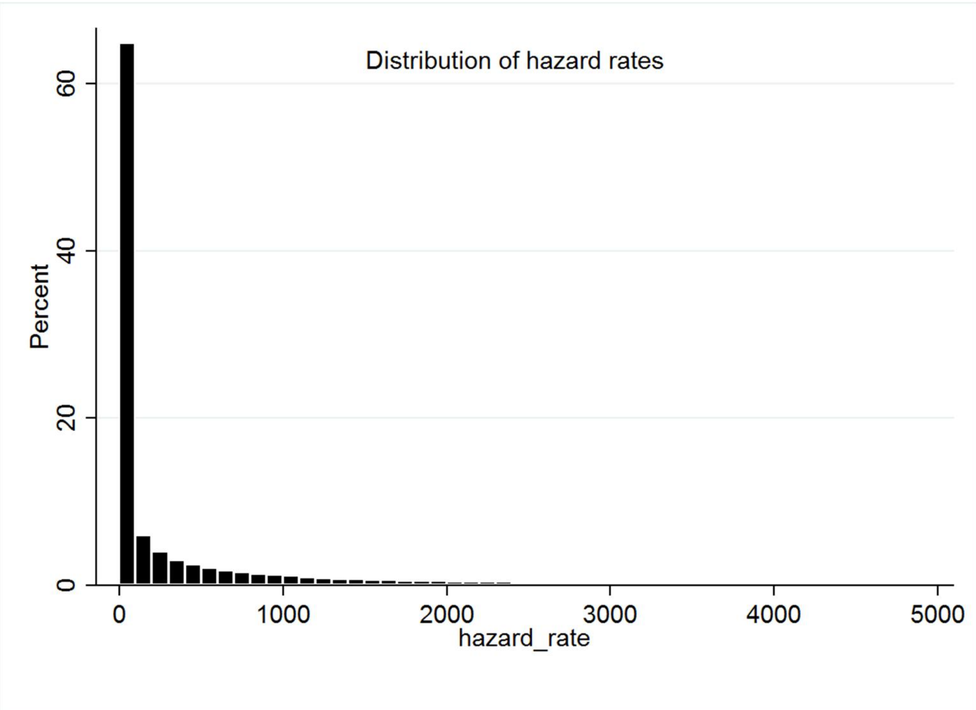
This section computes *hazard rates* for the individual trading accounts. *Hazard rate* is the message arrival intensity for a given stock, conditional on the time elapsed since the previous message. The concept of hazard rate was introduced by Hasbrouck and Saar (2011), who found out that the distribution of hazard rates is rapidly declining in time. Hasbrouck and Saar (2011) calculate the hazard rate as follows:

$HAZARD = t_n - t_{n-1}$ for $n = [2{,}3{,}4 \ldots N]$,where t_n denotes the timestamp value of message n.

This study uses a modified concept of the Hasbrouck and Saar (2011) hazard rate. The data used in this study allows identification of individual trading accounts, which makes it possible to compute the message arrival intensity conditional on the time elapsed since the previous message from another trading account. The hazard rate is a tool for estimating the reaction time of market participants to changes in the order book. Calculating the time since the previous message from another trading account makes the hazard rate a better tool for estimating reaction times since high frequency traders often post multiple messages instantaneously or in a very short time span, which can create bias in the hazard rate estimator. Also, hazard rates of zero milliseconds are omitted for the same reasons as they represent simultaneousness and do not reflect reaction times.

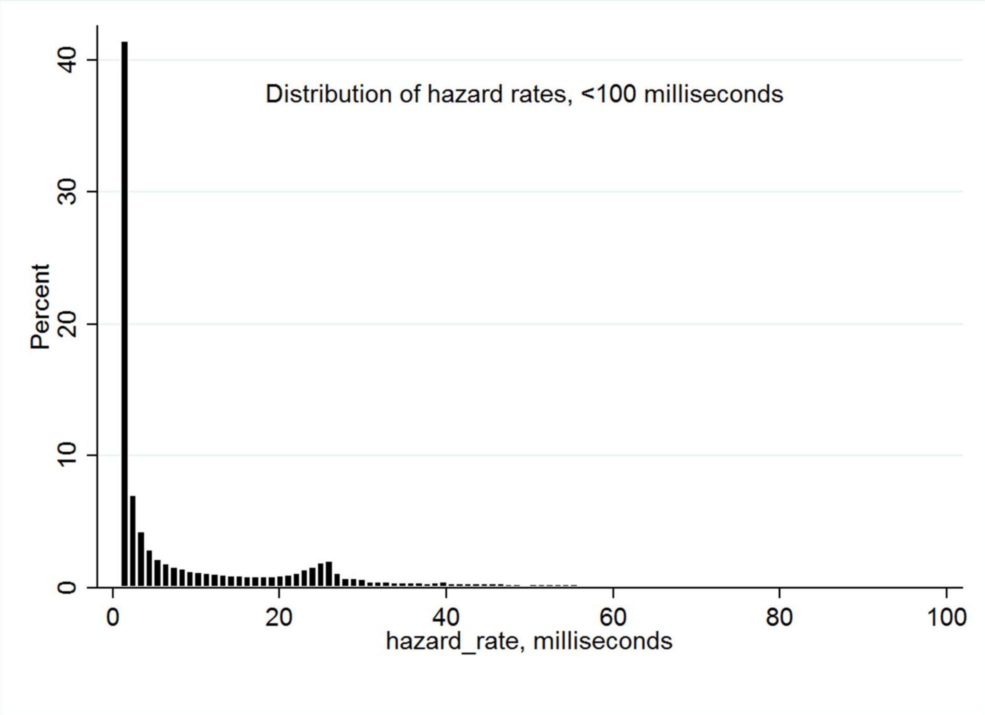
The h*azard rate* used in this study is calculated as follows:

$HAZARD_n = t_{n,i} - t_{n-1,i-1}$ for $n = [2,3,4 \ldots N]$,where $t_{n,i}$ denotes the timestamp value of message n of trading ID i, and $i - 1$ denotes an ID not equal to i.



Graph 7: Distribution of hazard rates in milliseconds, 0-5000ms.

Graph 7 plots the distribution of hazard rates for the sample period. The results derived here are similar to those of Hasbrouck and Saar (2011), who argue that hazard rates are declining in time since information intensity is also clustered and that trading intensity reflects changes in information. Keeping this in mind, the authors argue that with extremely low values, hazard rates do not reflect changes in information about firm fundamentals but about changes in market conditions. The data here suggests that hazard rates for the liquid stocks in NASDAQ OMX Nordic Exchange Helsinki are rapidly declining in the domain of under 200 milliseconds and declining modestly after that. The fact that over 60 per cent of all hazard rates are under 100 milliseconds suggests that most of the order flow activity is based on high frequency traders who react to changes in the order book.



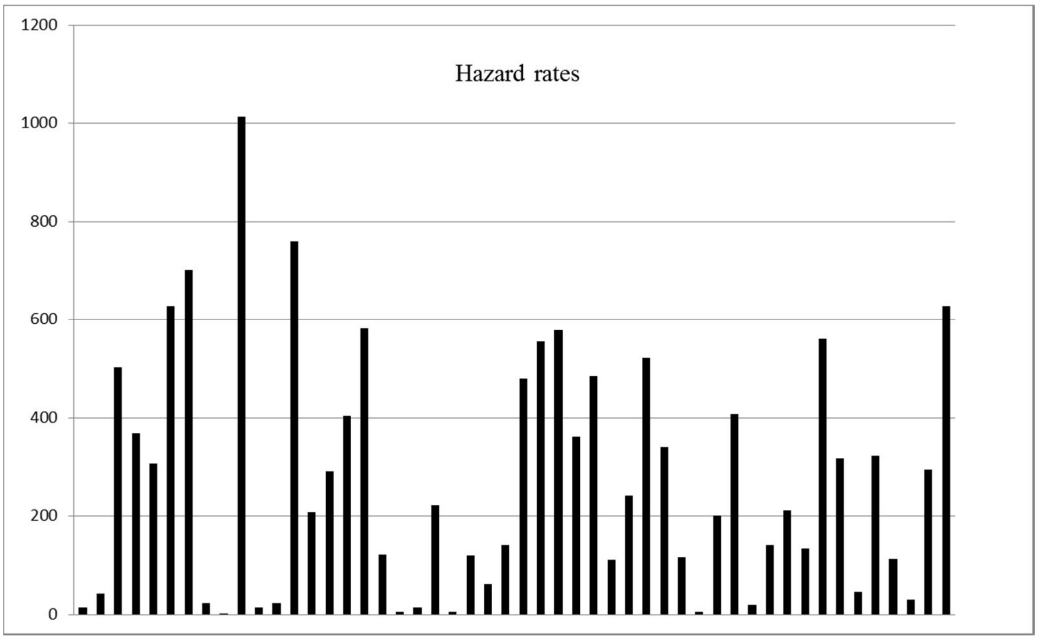
Graph 8: Distribution of hazard rates in milliseconds, 0-100ms.

Graph 8 plots the distribution of hazard rates in the domain of under 100 milliseconds. The hazard rates are rapidly declining in the domain of under 2 milliseconds, then slowly declining between 2 milliseconds and 20 milliseconds, and then increasing from 20 to 26 milliseconds, and then declining rapidly again. This hump in the distribution raises interesting questions about the reaction times of high frequency traders. It is reasonable to question if hazard rates of fewer than 2 milliseconds represent reaction times to order book events. Previous literature has reported reaction times as fast as 2-3 milliseconds (Hasbrouck & Saar 2011), but the extremely high proportion of hazard rates of under 2 milliseconds in the data raises the question if there are other factors driving down the hazard rates.

One possible explanation for the hazard rate dilemma is that the dynamics of the order book are too periodic for the hazard rate to reliably estimate reaction times to order book events. Suppose that an incoming market sell order $M_n$hits the trading system at time n removing a portion of the bid quote depth. Suppose further that a large number of high frequency traders react to the change in the order book by cancelling and posting new limit orders at time $n + x$, and that it takes time y to execute the whole updating operation so that some of the messages hit the trading system at time $n + x$ and some at time $n + x + y$. If the volume of the message traffic arising from the updating operation is sufficiently large, the hazard rate variable estimates y and not $n + x$, which represent the reaction time of high frequency traders.

If the above hypothesis holds true, then the hump in figure 10 can be thought as representing $n + x$, or the time it takes to react to market book changes, and the high proportion of hazard rates of under 2 milliseconds as representing y, or the time it takes for the high frequency traders to collectively execute their updating operations.

In order to identify high frequency traders, the mean hazard rate is calculated for each individual trading account. *Graph 9* plots the median hazard rates for the 50 most active trading accounts. A number of the most active trading accounts exhibit strikingly low median hazard rates, well below 10ms. Especially for the active trading accounts with a very high number of messages, a median hazard rate below 10ms stands as a reliable indicator for an ability to react to order book events extremely fast.



Graph 9: Median hazard rates by trading account for 50 most active trading accounts

5.5. Identified high frequency trading accounts in sample data

This section constructs an identifier for a high frequency trader using the data derived in the earlier section. The identifier uses the following data points: (1) amount of orders generated, (2) cancellation-order ratio, and (3) individual hazard rates.

Ideally, the high frequency identifier would use the average duration of non-zero positions and the average accumulated net positions in addition to the above measures to refine the identification process. Due to data limitations, these measures are only discussed in this context.

In order to use the data computed in the previous sections as criteria for labeling trading accounts as high frequency traders, arbitrary levels of those variables must be selected as cut-off values. As an arbitrary selection of the cut-off value can impose severe limitations to the results of this thesis, the level in each variable is chosen to be conservative enough to underestimate the amount of high frequency trading. To pass as a high frequency trading account, a trading account needs to:

i. Post over 5 percent of total daily average shares in at least one security
ii. Have a cancellation-order ratio of more than 95 per cent
iii. Have a mean or median hazard rate of less than 500ms.

Together these criteria produce six trading accounts that meet the definition of a high frequency trader without a question. Due to data confidentiality, these accounts are only referred to as *identified high frequency traders* in the rest of the study.

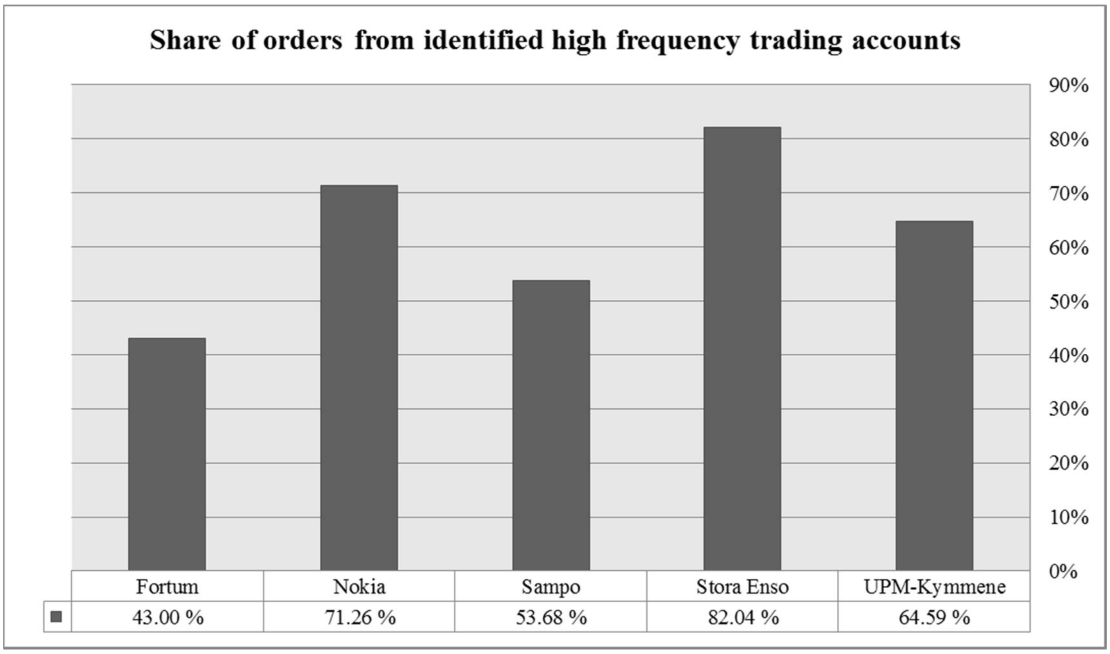
6 Findings and discussion

This chapter presents the empirical findings of the paper in the following order. First, the degree of high frequency trading in Helsinki Stock Exchange is reported in Section 6.1. After, the findings concerning the order generation characteristics of the identified high frequency trading accounts are presented in Section 6.2. Section 6.3 reports the limit order and cancellation arrival rates for high frequency trading accounts. Section 6.4 investigates the dynamics of high frequency trading order flow and cancellation arrival rates, and finally Section 6.5 investigates the relationship between high frequency trading order flow and stock price change.

6.1. The degree of high frequency trading in Helsinki Stock Exchange

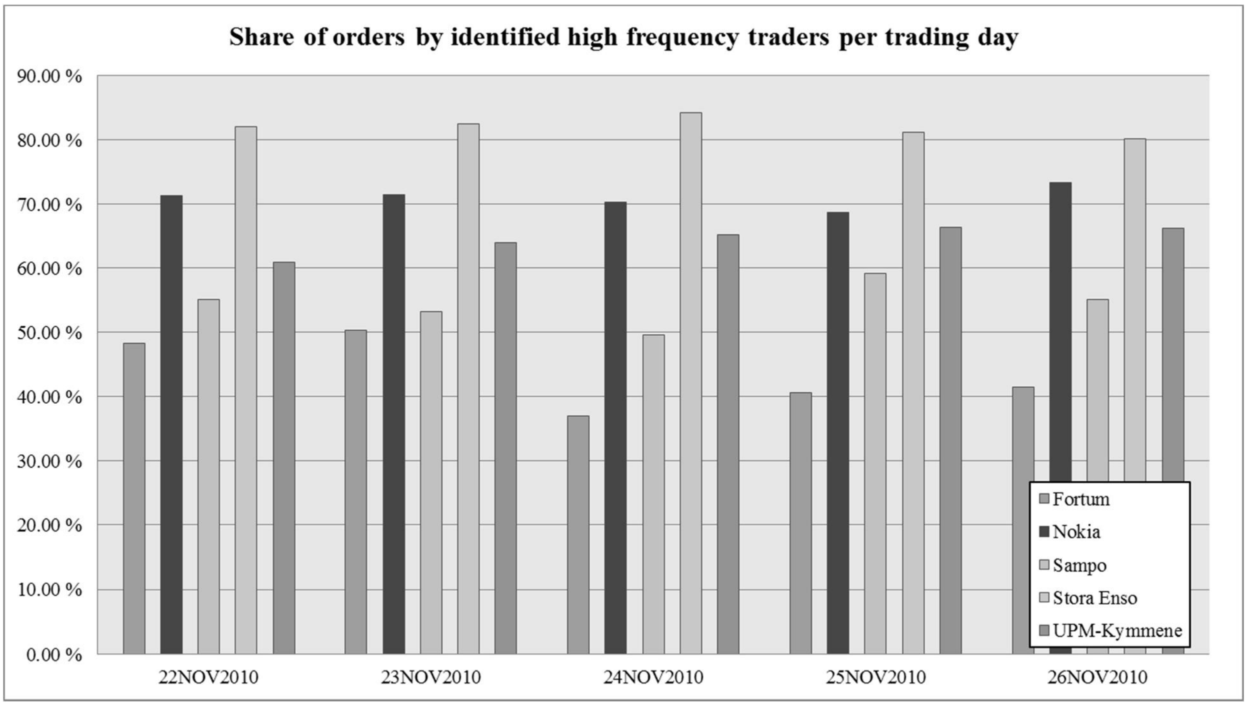
This section examines the degree of high frequency trading in Helsinki Stock Exchange by looking at the relative share of orders posted by *identified high frequency traders*. As the data does not allow tracking of trades by trading accounts, the share of orders is used as a proxy for the overall degree of high frequency trading. As high frequency trading strategies involve massive number of orders generated relative to actual trades, the share of orders posted by identified high frequency traders over-estimates the degree of high frequency trading in Helsinki Stock Exchange with respect to share of trading volumes. While this is a limitation to this study, studying pure order flow shares gives a reasonable estimate about the activity of high frequency traders. Gerig and Michayluk (2010) show that an automated liquidity provider, a high frequency trader in other words, transacts the majority of order flow in modern equity markets. Thus, order flow measures can be used to estimate the overall high frequency trading activity in a market.

Graph 10 gives the share of orders from identified high frequency trading accounts per stock in the sample data. The evidence suggests that high frequency trading is prominent in all of the stocks in the data sample, and that there exists significant variation across them. The difference between values for Stora Enso and Fortum is almost 40 percentage points, which suggests that high frequency traders are selective when it comes to choosing the securities in which they engage in their selected trading strategy. Given that the group of identified high frequency trading accounts only consists of a handful of trading accounts, the average number of orders generated by each of these accounts is high enough to assume that their primary trading strategy is electronic liquidity provisioning, or electronic market making in other words. It is also reasonable to assume that the high frequency trader identification of this study, which was conducted in a conservative manner so as not to overestimate the role of high frequency trading, left a number of high frequency trading accounts unidentified. In this case the order generation share of high frequency traders would be even larger than depicted here.



Graph 10: Share of orders by identified high frequency trading accounts

Graph 11 plots the share of orders from identified high frequency trading accounts for each trading day in the sample. The data suggests that high frequency trading activity is relatively stable over a five-day interval. One possible reason for this is that the most common trading strategy employed by high frequency traders in the sample data is electronic liquidity provisioning, where the activity of high frequency traders is mostly affected by the overall trading turnover rather than by information asymmetries, which would promote generally stable shares of high frequency trading. And with algorithmic trading in general, one would not expect to see significant deviations in the share of order flow captured by these traders since the algorithms execute a well-defined trading strategy from day to day. Hypothetically, largest drivers for deviations in the order flow volume of high frequency traders employing an electronic liquidity provision strategy would be changes in the overall trade and order flow activity in the stock. Thus it can be assumed that high frequency trading creates an increase in the overall order flow volume since competing high frequency traders respond to order book events created by ever more frequent updates by the other high frequency traders. This process will naturally lead to an increased share of order flow captured by high frequency traders, as seen in the data here.



Graph 11:Share of orders by identified high frequency trading accounts

Graph 12 plots the intra-day changes in high frequency trading activity. The share of high frequency orders are calculated for each 1-minute interval in a trading day and averaged within each stock. The trend in the time variation is examined by the following ordinary least squares regression:

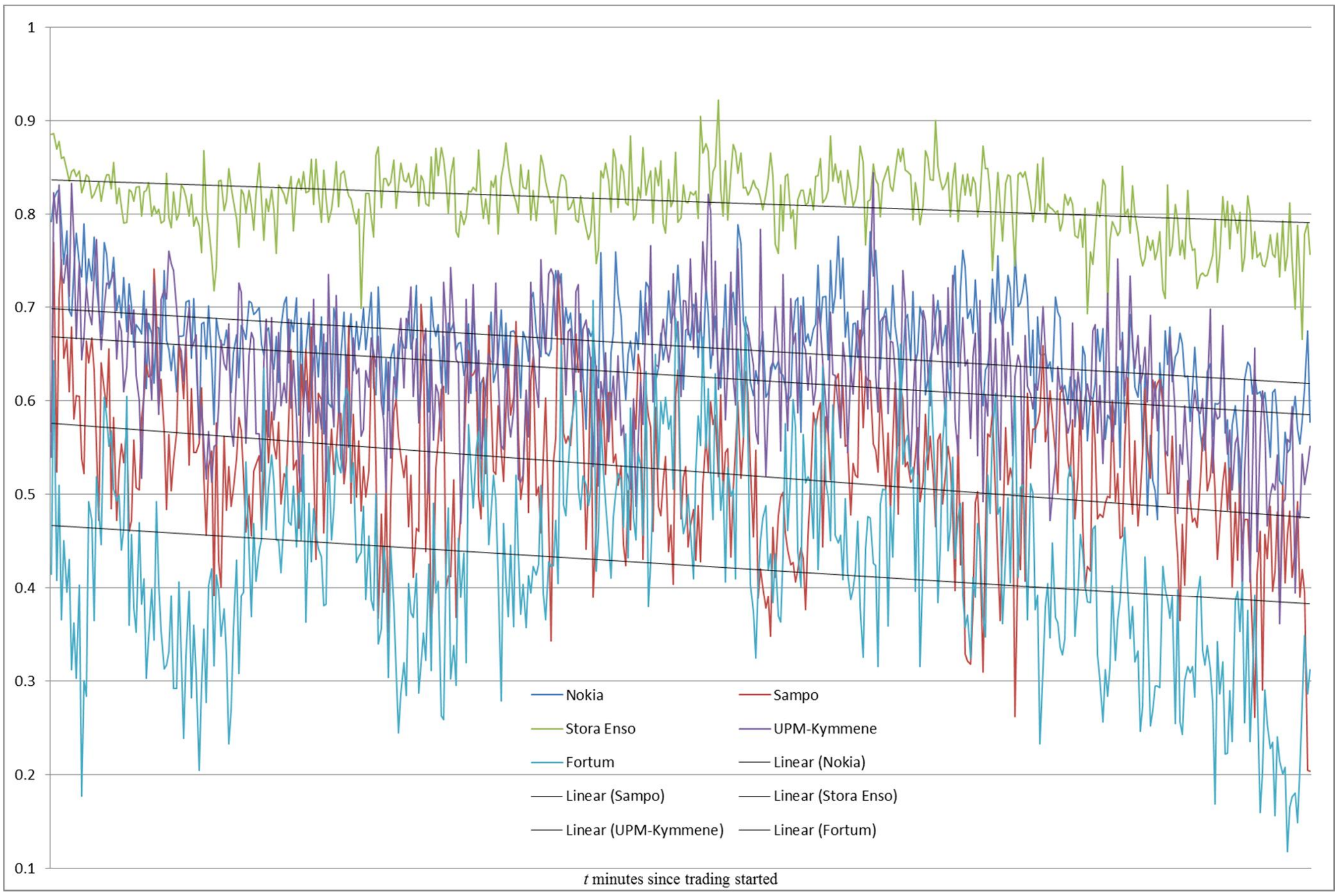
Regression (I)

$$y_i = \alpha_i + \beta_i minute + \varepsilon_i$$

	Fortum	Nokia	Sampo	Stora Enso	UPM-Kymmene
_cons	0.4664682	0.6981645	0.5759803	0.8365865	0.6682677
minute	-0.0001655	-0.0001585	-0.0001992	-0.0000911	-0.0001652
	(0.0000318)	(0.0000155)	(0.0000238)	(0.0000104)	(0.0000212)
t	-5.21	-10.24	-8.36	-8.79	-7.8

Table 5 Results of regression (I)

The results of Regression (I) suggest that the share of high frequency trading orders decreases as a trading day develops. The drop in the share during the last hours of trading is evident in all stocks studied while there is significant variation in the intensity of the declination. The declining share of high frequency trading suggests that these traders manage their inventories and reduce the aggressiveness of their trading algorithms in order to arrive to the end of the trading day with zero net positions. Given that one of the principal risks related to market making is the inventory risk, this finding further supports the hypothesis that these identified high frequency trading accounts mainly engage in electronic liquidity provisioning.

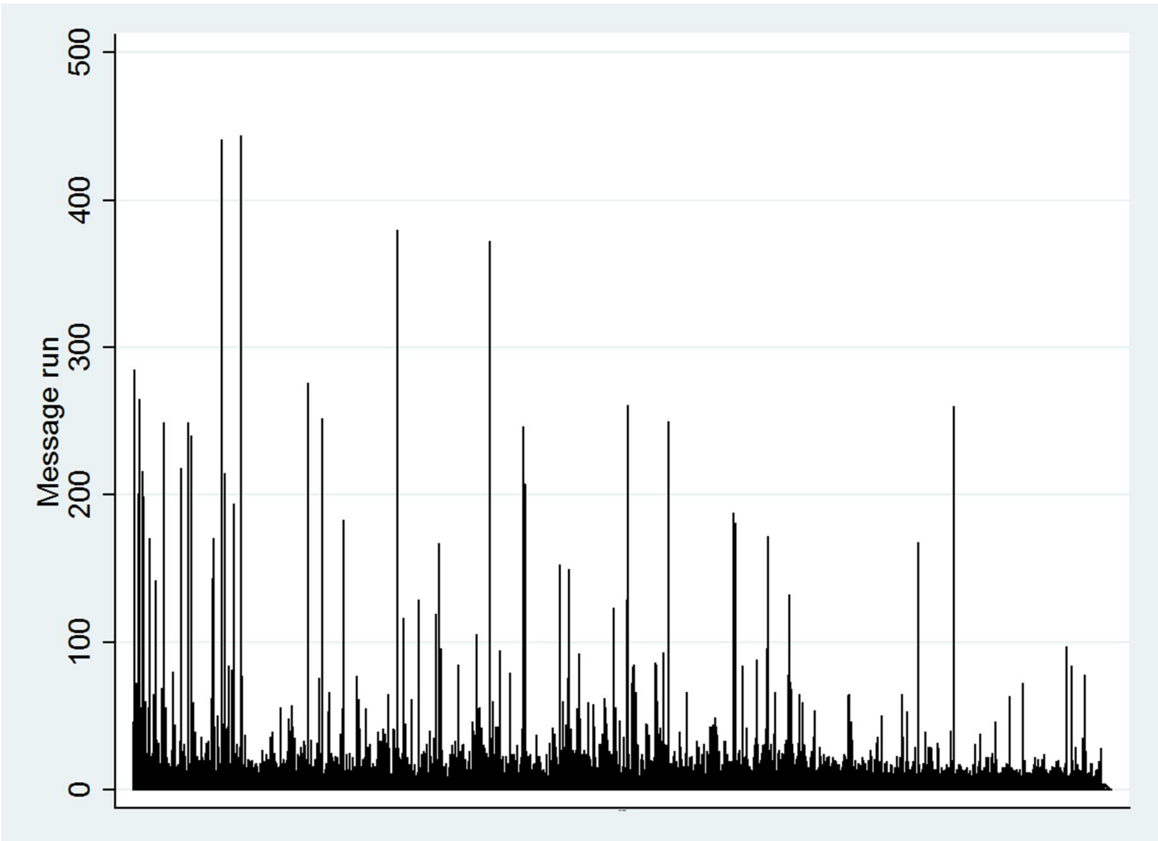


Graph 12: Average share of high frequency orders during 1-minute intervals in trading day

The findings suggest that a majority of the order flow in NASDAQ OMX Nordic Exchange Helsinki is generated by a handful of high frequency trading accounts identified in this study. While their activity may comprise of several trading strategies, the large amounts of orders generated by the high frequency traders and their declining order flow share as a trading day progresses make it reasonable to assume that at least one of the identified high frequency traders, and possible all of them, engage in the electronic liquidity provisioning strategy.

6.2. Order generation characteristics of identified high frequency trading accounts

High frequency traders need to constantly update their buy and sell order portfolio in accordance with changes in the limit order book. The sophisticated algorithms used by high frequency traders, together with low-latency connections offered by co-location services, enable them to cancel and submit large amounts of orders within a very short time interval. To capture the periodicity in the order submission dynamics, *message run* variable is calculated for the sample data. The message run identifies an uninterrupted chain of order submissions and cancellations originated by one identified high frequency trader. While some of the message run chain are relatively long in terms of consecutive messages, in the context of high frequency trading data these actions happen almost instantaneously. Given that this study has identified multiple competing high frequency traders, discovering frequent message runs of more than 50 consecutive messages suggests that at least one of them can post and cancel orders practically instantaneously.



Graph 13: Message runs against time (mstime) for the sample data

Graph 13 plots message runs for the sample data against time where the value on the y-axis represents the length of the run. The frequent message runs with many of them exceeding 100 consecutive messages suggests that the order submission dynamics of the high frequency traders is highly periodic. High periodicity supports the hypothesis that high frequency traders capture the majority of order flow by engaging in electronic liquidity provision strategy in which they adjust their buy and sell orders constantly. The relatively large number of lengthy runs may also suggest asymmetries in the latencies of the different high frequency traders. Suppose that one of the identified high frequency traders has a lower latency than the others. In other words, it can either access the market infrastructure with less delay or has the ability to process market information faster. In this case that high frequency trader would be able to update its quote offering before the others and thus create long *message runs*.

6.3. Limit order and cancellation arrival rates

This section presents the limit order and cancellation arrival rates for identified high frequency traders. The arrival rates are used to study the order generation and cancellation characteristics of high frequency traders. The arrival rates are denoted as

- $\check{\lambda}(i)$ for the arrival rate of limit orders with i ticks away from the best quote.
- $\breve{\theta}(i)$ for the arrival rate of cancellations with i ticks away from the best quote.

6.3.1. Limit order arrival rates

The limit order arrival rate is calculated as

$\check{\lambda}(i) = \frac{N_l(i)}{T}$ for $0 \leq i < 10$,

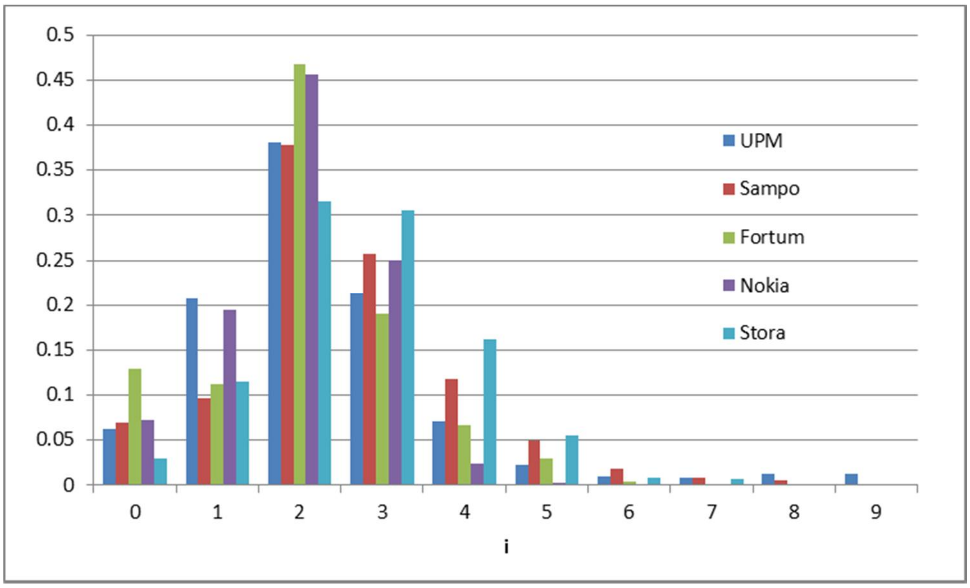
where $N_l(i)$ is the total number of limit orders that arrived at a distance (i) from the best quote and T is the total trading time in minutes. The arrival function captures both buy and sell limit orders so that a buy order 2 ticks below the current market bid price and a sell order 2 ticks above the current market ask price are recorded as same events.

Table 5 lists the limit order arrival rates for identified high frequency traders by stocks for $0 \geq i < 10$ ticks from the market bid/ask. The table tells how many limit orders identified high frequency traders post at *i* ticks away from the best prices. The data highlights the differences in the activity between stocks as the most traded stocks Nokia and Stora Enso have combined arrival rates of more than ten times those of Fortum, the least traded stock in the sample. Another important finding is that most of the incoming orders arrive away from the best bid/ask price, a finding made also in previous literature (Cvitanic & Kirilenko, 2010, Potter & Bouchaud, 2002).

Limit order		*Fortum*	*Nokia*	*Sampo*	*Stora*	*UPM*
i	*0*	*0.971667*	*9.355741*	*1.227778*	*3.648148*	*1.162222*
	1	*0.83963*	*25.23759*	*1.725556*	*14.2063*	*3.855185*
	2	*3.51*	*59.18056*	*6.737407*	*38.7687*	*7.042037*
	3	*1.431111*	*32.50333*	*4.574074*	*37.65056*	*3.943148*
	4	*0.497593*	*3.166296*	*2.096296*	*19.87759*	*1.303889*
	5	*0.217963*	*0.3*	*0.878519*	*6.855741*	*0.406111*
	6	*0.033704*	*0.032407*	*0.325*	*1.083519*	*0.18963*
	7	*0.007222*	*0.005556*	*0.149259*	*0.835185*	*0.162037*
	8	*0.002222*	*0.002593*	*0.096481*	*0.189074*	*0.241667*
	9	*0.001667*	*0.004444*	*0.016111*	*0.079815*	*0.222037*

Table 5:Limit order arrival rates for identified high frequency traders

Graph 14 illustrates the shape of the distribution of limit order arrivals by plotting the arrival rates for high frequency traders relative to the total limit order arrivals for $0 \geq i < 10$. The data reveals that the shape of the limit order arrival distribution is relatively harmonious for all stocks in the sample. Most of the limit orders from high frequency traders arrive at $i = 2$ ticks away from the current best price. The share of incoming limit orders at the best available price is very low, just over 7 per cent on average. The distribution then rises steeply and peaks at 2 ticks away from the best price and then descends until between 3 and 5 ticks away from the best price before the so called tail begins. This suggests that majority of the high frequency trading order flow takes place away from the front of the order book but does not deviate far away from it.



Graph 14: Relative limit order arrivals for high frequency traders

6.3.2. Cancellation arrival rates

Because the cancellation rate is proportional to the amount of orders at a particular price level, the steady state of the order book, Q_i, must be calculated first. The steady state gives the average amount of orders at a distance (i) from the best quote. The steady state is calculated as

$$Q_i \quad = \frac{1}{M}\sum_{j=1}^{M} S_{ij} \text{ for } 0 \leq i < 10,$$

where M is the number of quote rows and S_i is the amount of outstanding shares bid at a distance (i) from the best quote for both buy and sell queues.

The cancellation rate is then calculated as

$$\breve{\theta}(i) = \frac{N_{c(i)}S_{c(i)}}{TQ_i} \text{ for } 0 \leq i < 10,$$

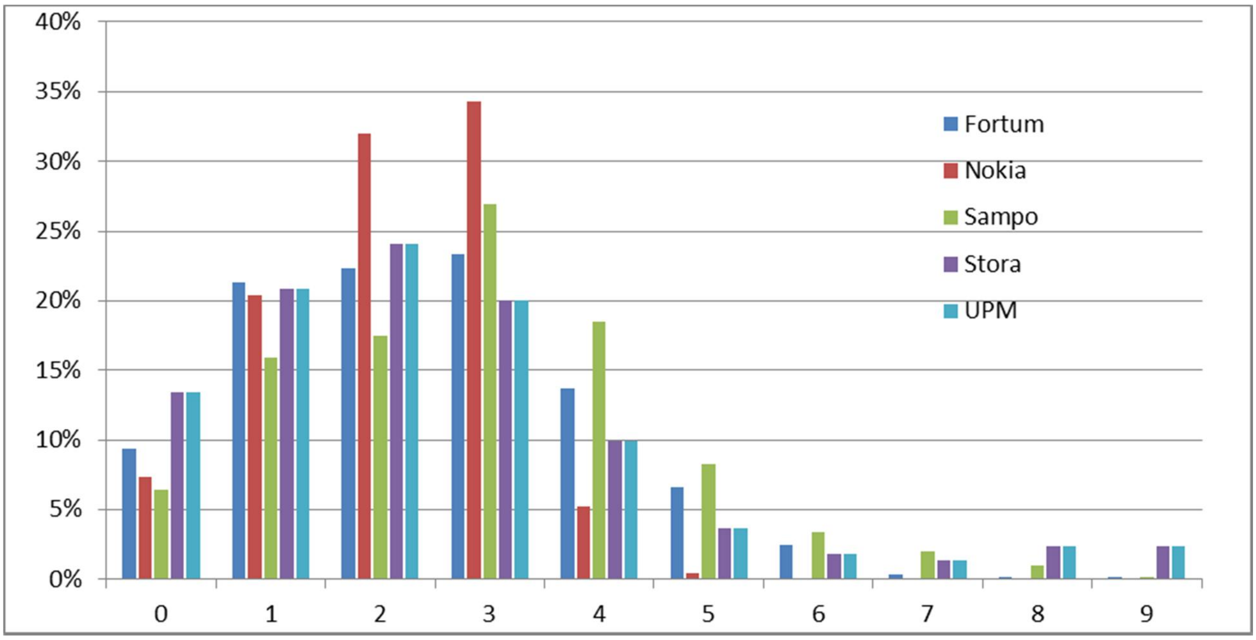
where $N_{c(i)}$ is the number of cancellations at a distance (i) from the best quote, $S_{c(i)}$ is the average size of the cancellation at a distance (i) from the best quote, T is total trading time in minutes and Q_i is the average queue size at a distance (i) from the best quote.

Table 6 lists the cancellation arrival rates for identified high frequency traders in each stock. The numbers give the relation of average quantity cancelled at given distance (i) from the best quote in a minute and the average queue size at distance (i) from the best quote. In other words, a unit value would indicate a 100 per cent cancellation turnaround per minute.

Cancellation arrival		Fortum	Nokia	Sampo	Stora	UPM
i	0	0.13	0.61	0.20	0.28	0.28
	1	0.30	1.70	0.48	0.43	0.43
	2	0.32	2.67	0.53	0.49	0.49
	3	0.33	2.85	0.82	0.41	0.41
	4	0.19	0.44	0.56	0.20	0.20
	5	0.09	0.04	0.25	0.07	0.07
	6	0.04	0.01	0.10	0.04	0.04
	7	0.01	0.00	0.06	0.03	0.03
	8	0.00	0.00	0.03	0.05	0.05
	9	0.00	0.01	0.01	0.05	0.05

Table 6: Cancellation arrival rates for high frequency traders

Graph 15 plots the cancellation arrival rates as relative values of the sum of the arrival rates for $0 \leq i < 10$. The data suggests that in relation to the steady state of the order book, most cancellation occurs away from the front of the order book but relatively close to it. In other words, the average cancellation turnaround increases as we move away from the front of the order book but decreases after 3 ticks.



Graph 15: Relative distribution of cancellation arrival rates

6.4. Arrival rate dynamics

This section investigates the dynamics of limit order and cancellation arrival rates of the identified high frequency trading accounts. By looking at these dynamics, it is possible to see if some events have a tendency to lead to other events and if there are tendencies for contemporaneous movements in the arrival rate time series.

For each stock and trading day, limit order and cancellation arrival rates with $0 \leq i < 4$ ticks away from the current best prices are recorded for each 100 millisecond time interval t. Then the dynamics of the arrival rates and the best bid and ask prices for each period are studied by the following VAR-model:

REGRESSION (II)

Let $\mathbb{Y}_t = (\mathrm{y}_{1t}, \mathrm{y}_{2t}, \dots, \mathrm{y}_{22t})$ denote an $(22\ x\ 1)$ vector of the time series variables:

- y_{1t}=arrival_Bi_0 (Total quantity of buy orders at best bid price during period t)
- y_{2t}=arrival_Bi_1(Total quantity of buy orders at best bid price +1 tick during period t)
- y_{3t}=arrival_Bi_2
- y_{4t}=arrival_Bi_3
- y_{5t}=arrival_Bi_4
- y_{6t}=arrival_Si_0 (Total quantity of sell orders at best ask price during period t)
- y_{7t}=arrival_Si_1
- y_{8t}=arrival_Si_2
- y_{9t}=arrival_Si_3
- y_{10t}=arrival_Si_4
- y_{11t}=arrival_CBi_0 (Total quantity of cancelled buy orders at best bid price during period t)
- y_{12t}=arrival_CBi_1
- y_{13t}=arrival_CBi_2
- y_{14t}=arrival_CBi_3
- y_{15t}=arrival_CBi_4
- y_{16t}=arrival_CSi_0 (Total quantity of cancelled sell orders at best ask price during period t)
- y_{17t}=arrival_CSi_1

- y_{18t}=arrival_CSi_2
- y_{19t}=arrival_CSi_3
- y_{20t}=arrival_CSi_4
- y_{21t}=bid_C (change in the best bid price during period t)
- y_{22t}=ask_C (change in the best ask price during period t)

Then the VAR model can be expressed as

$$\mathbb{Y}_t = c + \Pi Y_{t-1} + \varepsilon_t$$

where c is the constant term and Π is a $(22\ x22)$ matrix including all the coefficients. In other terms each endogenous variable is estimated by its own lagged values and lagged values of all the other variables.

The results of Regression (II) are provided in Appendix B. Because of space limitations, the results are provided for one stock only, but identical results are found for the whole sample. An example of the results is provided here. *Graph 16* gives the example VAR regression estimates for Regression (II). The left hand side variable is the quantity of incoming sell orders at two ticks away from the best ask price. The results show for example, that an increase in the best ask price at period $t-1$ reduces the amount of incoming sell orders with two ticks away from the best ask price. It is worth noting that cancellations are reported as negative numbers in the data, so that a negative coefficient for a cancellation measure indicates increased cancellation quantity.

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
arrival_Si_2						
bid_c						
L1.	-7.885113	6.081601	-1.30	0.195	-19.80483	4.034606
ask_c						
L1.	-23.02376	6.781262	-3.40	0.001	-36.31479	-9.732736
arrival_Bi_0						
L1.	.1629438	.1815734	0.90	0.370	-.1929336	.5188212
arrival_Bi_1						
L1.	-.436053	.1102793	-3.95	0.000	-.6521965	-.2199096
arrival_Bi_2						
L1.	.0520987	.0353671	1.47	0.141	-.0172196	.1214169
arrival_Bi_3						
L1.	.047776	.0280491	1.70	0.089	-.0071992	.1027512
arrival_Bi_4						
L1.	-.0001281	.0429394	-0.00	0.998	-.0842879	.0840316
arrival_Si_0						
L1.	-.151531	.2556724	-0.59	0.553	-.6526398	.3495777
arrival_Si_1						
L1.	.1601682	.1269044	1.26	0.207	-.0885599	.4088963
arrival_Si_2						
L1.	.0829792	.0297596	2.79	0.005	.0246515	.1413069
arrival_Si_3						
L1.	-.0457946	.0230217	-1.99	0.047	-.0909163	-.0006728
arrival_Si_4						
L1.	-.1465527	.0383314	-3.82	0.000	-.2216809	-.0714245
arrival_CB~0						
L1.	-.0886029	.2035308	-0.44	0.663	-.487516	.3103101
arrival_CB~1						
L1.	-.1641631	.0862134	-1.90	0.057	-.3331383	.0048122
arrival_CB~2						
L1.	-.0396756	.0373544	-1.06	0.288	-.112889	.0335377
arrival_CB~3						
L1.	.000512	.0317367	0.02	0.987	-.0616907	.0627147
arrival_CB~4						
L1.	-.0432464	.0464748	-0.93	0.352	-.1343353	.0478426
arrival_CS~0						
L1.	.383858	.1958276	1.96	0.050	.000043	.767673
arrival_CS~1						
L1.	.0000424	.1035048	0.00	1.000	-.2028234	.2029081
arrival_CS~2						
L1.	-.3122865	.0346157	-9.02	0.000	-.380132	-.244441
arrival_CS~3						
L1.	-.1541723	.0281036	-5.49	0.000	-.2092544	-.0990902
arrival_CS~4						
L1.	-.0953404	.0357644	-2.67	0.008	-.1654373	-.0252434
_cons	398.5928	91.68608	4.35	0.000	218.8913	578.2942

Graph 16: Example of results of Regression (II)

Perhaps the most interesting dynamic is found between the arrival rates of limit orders and cancellations with same distance from the best bid/ask price. The complete regression results show that an increase in the arrival rate of buy limit orders at distance j from the best bid price at period $t-1$ increases the arrival rate of buy order cancellations at distance j from the best bid at period t. The same is true for sell limit orders, where past limit order flow increases the cancellation rate with the same distance the following period. Given that the time period used is 100ms, this implies that the identified high frequency trading accounts often cancel their limit orders within a timespan of 200ms.

Interestingly, a similar feedback is found to exist in the opposing direction. The results suggest that an increase in the buy (sell) cancellation arrival rate at distance j from the best price leads to an increase in the buy (sell) limit order arrival rate with the same distance during the next period. These results suggest two discernible behavioral patterns in the order flow of the identified high frequency traders. On one hand they react to limit order book events such as an increase in the bid or ask price by cancelling their existing orders, which is followed by increased arrival rates of new limit orders in the period following the cancellation. On the other hand they often cancel their limit orders rapidly, within a timespan of 200ms, a practice known as “pinging”. These rapid messages to the system can be used for tracking hidden liquidity, for “sniping” other orders, or to distort other limit order signals.

6.5. Arrival rates and stock price behavior

This section investigates the short-term effects of high frequency trading order flow on stock price. Order flow is measured by arrival rates of limit orders with $0 \leq i < 5$ ticks away from the current best prices, and only limit orders coming from the identified high frequency traders are counted. Each stock is studied individually, and each trading day is divided into t time intervals.

For each time interval t, the following variables are calculated:

- Limit buy order arrival rates with $0 \leq i < 5$ ticks away from the best price
- Limit sell order arrival rates with $0 \leq i < 5$ ticks away from the best price
- Percentage increase in midprice during interval t

Then, the following OLS regression is estimated for each stock and each trading day. The results of the regressions are reported in Appendix B.

REGRESSION (III)

$$\begin{aligned} MIDPRICE\_CHANGE_t \\ &= \beta_1 + \beta_{2i} LIMIT\_BUY\_ORDER\_ARR\_RATE_{i,t-1} \\ &+ \beta_{3i} LIMIT\_SELL\_ORDER\_ARR\_RATE_{i,t-1} + \varepsilon_t \end{aligned}$$

The regression specification uses lagged variables for order arrival rates and checks if the order flow behavior of the identified high frequency trading accounts influences stock price in the short term. After extensive studies with different time period lengths, it seems that for the less traded stocks Sampo, Fortum, and UPM, past order flow predicts future stock price change with time period t set around 100-150ms. For Stora Enso, past order flow seems to predict future stock price change with t set around 60-80ms, and for Nokia no statistically significant relationship is found with any time period t value.

The results indicate that increased arrival rates in the front of the order book on buy side predict higher stock price in the following period, while increased arrival rates in the front of the order book on sell side predict lower stock price in the following period. The front of the order book refers here to limit orders arriving at the best current bid/ask price or at most one tick away from it. The effect is opposite for the back of the order book, which in this context refers to limit orders arriving at 4 or 5 ticks away from the best price. For these arrival rates, an increased rate on buy side often leads to lower stock price in the following period, while an increased rate on sell side leads to higher stock price. These effects, however, were not statistically significant across the whole sample but showed significant variation in results.

The three less traded stocks Sampo, Fortum, and UPM also exhibit smaller degrees of HFT activity, as was shown in Chapter 6.1. This leads to an interesting question of whether these three stocks show a relationship between high frequency trading order flow and stock price change with higher t values because of smaller degree of high frequency trading activity. It is logical to assume that more traded stocks with better market quality, such as Stora Enso and Nokia, would show no relationship of this kind, or at least weaker relationship. A relationship with smaller time period length can be regarded as weaker because it implies that the relationship only holds for a short period of time.

The results of regression (II) show that there exists a short-term relationship between high frequency trading order flow and stock price, but the results are not uniform within stocks in the sample. For some stocks the high frequency trading order flow around the best bid/ask prices is a significant predictor of future stock price. Further studies should investigate this relationship more carefully in order to better understand the effects of high frequency trading on market quality.

7 Conclusion

This study investigates the degree of high frequency trading in Helsinki Stock Exchange by identifying high frequency trading accounts from order level data. The findings of this study indicate that a handful of high frequency traders using sophisticated algorithms and accessing the marketplace with very low latencies dominate the limit order book. Together, the trading accounts identified as high frequency traders capture a majority of order flow in Helsinki Stock Exchange, up to 82 per cent of all orders, depending on the stock in question.

The high frequency traders' order generation is highly periodic, as measured with message runs. The high periodicity indicates that the high frequency traders react to changes in the order book by simultaneously updating a vast amount of their existing orders. Further, this study finds two discernible dynamics in the high frequency traders' order flow behavior. On one hand their limit order cancellations are followed by new limit order messages within time period of 200ms. On the other hand they often cancel their limit orders rapidly after placing a limit order in the system, which suggests a process of constant offering renewal.

The results of this study also indicate that there exists a weak short-term relationship between high frequency trading order flow and stock price change. The results suggests that increased limit order arrival rates for buy orders tend to increase the stock price, and increased limit order arrival rates for sell order to decrease the stock price. The duration of this relationship varies from 150ms to 60ms, depending on the security, and is non-existent for the most liquid share in the sample.

Possible limitations to this study may arise from two sources. On one hand, the identification process of the high frequency trading accounts relies on arbitrarily chosen levels with respect to order flow shares, cancellation rates and hazard rates. While these levels were deliberately chosen conservatively so as not to overestimate the degree of high frequency trading, the arbitrary levels may expose the findings of this study to considerable measurement error. Future studies about the topic should address these issues by using richer data that allows for calculating more precise measures for identification.

On the other hand, estimating the degree of high frequency trading in Helsinki Stock Exchange by looking only at the order flow data imposes limitations to this study as order flow measures may significantly overestimate the degree of high frequency trading in terms of traded shares.

References

Abate, J., Whitt, W. (1999). Computing Laplace transforms for numerical inversion via continued fractions. INFORMS J. Comput. 11(4) 394–405.

Aldridge, I. (2010). High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems. John Wiley & Sons.

Angel, J. J., and McCabe, D. M. (2010). Fairness in Financial Markets: The Case of High Frequency Trading. Johnson School Research Paper Series No. 08-2011.

Arnuk, S., and Saluzzi, J. (2010). Why Institutional Investors Should Be Concerned about High Frequency Traders. White Paper, Themis Trading LLC, July 9, 2009.

ASIC. (2010). Australian equity market structure. Australian Securities & Investment Commission, Report 215.

Bouchaud, J., Mezard, M., and Potters, M. (2002). Statistical Properties of Stock Order Books: Empirical Results and Models. Working Paper.

Brogaard, J. (2011a). The Activity of High Frequency Traders. Working Paper.

Brogaard, J. (2011b). High Frequency Trading and Volatility. Working Paper.

Cartea, A., and Penalva, J. (2011) Where is the value in high frequency trading? Working paper, Universidad Carlos III de Madrid.

Castura, J., Litzenberger, R., Gorelick, R. and Dwivedi, Y. (2010). Market efficiency and microstructure evolution in U.S. equity markets: a high frequency perspective. Working paper, RGM Advisors, LLC.

Cont, R., Stoikov, S., and Talreja, R. (2008). A Stochastic Model for Order Book Dynamics. Working Paper.

Cont, R., Kukanov, A., and Stoikov, S. (2011). The Price Impact of Order Book Events. Working Paper.

Cvitanic, J., and Kirilenko, A. (2010). High Frequency Traders and Asset Prices. Working Paper.

Easley, D., Lopez de Prado, M. M., and O'Hara, M. (2011). The Microstructure of the ‘Flash Crash’: Flow Toxicity, Liquidity Crashes and the Probability of Informed Trading. The Journal of Portfolio Management, Vol. 37, No. 2, pp. 118-128, Winter 2011.

Financial Services Authority. (2011). Decision Note 6.5.2011.

Gerig, A., and Michayluk, D. (2010). Automated Liquidity Provision and the Demise of Traditional Market Making. Working Paper.

Gomber, P., Arndt, B., Lutat, M., and Uhle, T. (2011). High-Frequency Trading. Study Report.

Harris, L. (2003) Trading and exchanges. Market microstructure for practitioners, Oxford University Press, Oxford.

Hasbrouck, J., and Saar, G. (2011). Low-Latency Trading. Johnson School Research Paper Series No. 35-2010; AFA 2012 Chicago Meetings Paper.

Hendershott, T., and Riordan, R. (2009). Algorithmic trading and information. NET Institute Working Paper No. 09-08.

IOSCO. (2011). TECHNICAL COMMITTEE OF THE INTERNATIONAL ORGANIZATION OF SECURITIES COMMISSIONS. Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency, Consultation Report.

Jarrow, R. A., and Protter, P. (2011). A Dysfunctional Role of High Frequency Trading in Electronic Markets. Johnson School Research Paper Series No. 08-2011.

Kirilenko, A. A., Kyle, A. S., Samadi, M., and Tuzun, T. (2011). The Flash Crash: The Impact of High Frequency Trading on an Electronic Market. Working Paper.

Kearns, M., Kulesza, A., and Nevmyvaka, Y. (2010). Empirical Limitations on High Frequency Trading Profitability. Working Paper.

Liu, W. (2009) Monitoring and limit order submission risks. Journal of Financial Markets, Volume 12, Issue 1, February 2009, Pages 107-141.

Love, R., and Payne, R. G. (2006). Macroeconomic News, Order Flows and Exchange Rates. Working Paper.

Menkveld, A. J. (2011). High Frequency Trading and The New-Market Makers. EFA 2011 Paper.

SEC. (2010). Securities and Exchange Commission Concept Release on Equity Market Structure, January 14, 2010.

Potters, M., and Bouchaud , J. (2002). More Statistical Properties of Order Books and Price Impact. Working Paper.

Vega, C. (2007). Informed and Strategic Order Flow in the Bond Markets. The Review of Financial Studies, Vol. 20, Issue 6, pp. 1975-2019, 2007.

Zovko, I. I., and Farmer, J. D. (2002). The Power of Patience: A Behavioral Regularity in Limit Order Placement. Working Paper.

Zhang, F. (2010). High-Frequency Trading, Stock Volatility, and Price Discovery. Working Paper.

APPENDIX A: Results for regression (II)

Because of space limitations, results are showed for one stock and trading day: Nokia 26th November. Results are similar for other stocks and trading days as well.

```
Vector autoregression

Sample:  1222 - 269938, but with gaps             No. of obs      =      1884
Log likelihood = -334298.7                        AIC             =   355.419
FPE            =  1.7e+127                        HQIC            =  355.9671
Det(Sigma_ml)  =  1.0e+127                        SBIC            =  356.9072
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
bid_c	23	8.54064	0.1369	298.8084	0.0000
ask_c	23	4.14431	0.0162	30.9359	0.0974
arrival_Bi_0	23	521.174	0.0255	49.33676	0.0007
arrival_Bi_1	23	1233.69	0.1460	322.0926	0.0000
arrival_Bi_2	23	3763.64	0.1238	266.2268	0.0000
arrival_Bi_3	23	2584.96	0.0715	145.1391	0.0000
arrival_Bi_4	23	499.563	0.5248	2080.677	0.0000
arrival_Si_0	23	573.635	0.0534	106.2632	0.0000
arrival_Si_1	23	1434.82	0.0634	127.608	0.0000
arrival_Si_2	23	4065.78	0.1396	305.5563	0.0000
arrival_Si_3	23	3652.86	0.0517	102.7917	0.0000
arrival_Si_4	23	650.63	0.0240	46.25012	0.0018
arrival_CBi_0	23	545.29	0.1754	400.7318	0.0000
arrival_CBi_1	23	1264.56	0.2748	713.8995	0.0000
arrival_CBi_2	23	2995.83	0.1180	252.0088	0.0000
arrival_CBi_3	23	2246.2	0.1164	248.1844	0.0000
arrival_CBi_4	23	526.067	0.3920	1214.626	0.0000
arrival_CSi_0	23	476.352	0.1853	428.6261	0.0000
arrival_CSi_1	23	1632.34	0.2244	545.149	0.0000
arrival_CSi_2	23	3611.14	0.0588	117.7804	0.0000
arrival_CSi_3	23	3076.98	0.0719	145.9959	0.0000
arrival_CSi_4	23	917.515	0.2837	746.0492	0.0000

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
bid_c						
bid_c						
L1.	-.245809	.014835	-16.57	0.000	-.274885	-.2167329
ask_c						
L1.	.115661	.018819	6.15	0.000	.0787765	.1525456
arrival_Bi_0						
L1.	.0008961	.0003738	2.40	0.017	.0001635	.0016288
arrival_Bi_1						
L1.	-.0000897	.0001551	-0.58	0.563	-.0003937	.0002143
arrival_Bi_2						
L1.	.0000327	.0000622	0.53	0.599	-.0000892	.0001546
arrival_Bi_3						
L1.	7.87e-06	.0000706	0.11	0.911	-.0001305	.0001463
arrival_Bi_4						
L1.	-5.13e-06	.0003553	-0.01	0.988	-.0007015	.0006912
arrival_Si_0						
L1.	.0001001	.0004625	0.22	0.829	-.0008064	.0010067
arrival_Si_1						
L1.	-.0000441	.0001457	-0.30	0.762	-.0003298	.0002415
arrival_Si_2						
L1.	-6.20e-06	.0000562	-0.11	0.912	-.0001164	.000104
arrival_Si_3						
L1.	.0000216	.000067	0.32	0.748	-.0001097	.0001529
arrival_Si_4						
L1.	.0000913	.000165	0.55	0.580	-.0002321	.0004147
arrival_CB~0						
L1.	.0011848	.0004447	2.66	0.008	.0003131	.0020564
arrival_CB~1						
L1.	.0000496	.00012	0.41	0.679	-.0001855	.0002847
arrival_CB~2						
L1.	-.0000146	.0000723	-0.20	0.840	-.0001564	.0001272
arrival_CB~3						
L1.	.0000531	.0000816	0.65	0.515	-.0001068	.000213
arrival_CB~4						
L1.	-.0004294	.0003683	-1.17	0.244	-.0011512	.0002925
arrival_CS~0						
L1.	.0001732	.0005492	0.32	0.752	-.0009032	.0012496
arrival_CS~1						
L1.	.0000593	.0001471	0.40	0.687	-.0002289	.0003476
arrival_CS~2						
L1.	-.0000416	.0000669	-0.62	0.534	-.0001728	.0000895
arrival_CS~3						
L1.	.0000388	.0000691	0.56	0.574	-.0000966	.0001742
arrival_CS~4						
L1.	-.0001366	.0002004	-0.68	0.496	-.0005293	.0002562
_cons	-.3212594	.2278126	-1.41	0.158	-.7677638	.1252451

ask_c						
bid_c						
L1.	-.0007201	.0071986	-0.10	0.920	-.0148291	.0133889
ask_c						
L1.	-.0188153	.0091318	-2.06	0.039	-.0367134	-.0009173
arrival_Bi_0						
L1.	-.0000388	.0001814	-0.21	0.831	-.0003943	.0003167
arrival_Bi_1						
L1.	-.0001339	.0000753	-1.78	0.075	-.0002814	.0000137
arrival_Bi_2						
L1.	-.0000593	.0000302	-1.96	0.050	-.0001184	-1.06e-07
arrival_Bi_3						
L1.	-4.96e-07	.0000343	-0.01	0.988	-.0000677	.0000667
arrival_Bi_4						
L1.	-.0000182	.0001724	-0.11	0.916	-.0003561	.0003197
arrival_Si_0						
L1.	-.0002588	.0002244	-1.15	0.249	-.0006986	.0001811
arrival_Si_1						
L1.	-.0000234	.0000707	-0.33	0.741	-.000162	.0001153
arrival_Si_2						
L1.	1.17e-07	.0000273	0.00	0.997	-.0000534	.0000536
arrival_Si_3						
L1.	-5.68e-06	.0000325	-0.17	0.861	-.0000694	.000058
arrival_Si_4						
L1.	.000053	.0000801	0.66	0.508	-.0001039	.00021
arrival_CB~0						
L1.	.0002763	.0002158	1.28	0.200	-.0001466	.0006993
arrival_CB~1						
L1.	.0000551	.0000582	0.95	0.344	-.000059	.0001692
arrival_CB~2						
L1.	-.0000356	.0000351	-1.02	0.310	-.0001044	.0000332
arrival_CB~3						
L1.	3.87e-06	.0000396	0.10	0.922	-.0000737	.0000815
arrival_CB~4						
L1.	-.0000293	.0001787	-0.16	0.870	-.0003796	.0003209
arrival_CS~0						
L1.	.0001095	.0002665	0.41	0.681	-.0004128	.0006318
arrival_CS~1						
L1.	-.0000557	.0000714	-0.78	0.435	-.0001956	.0000841
arrival_CS~2						
L1.	-.0000155	.0000325	-0.48	0.634	-.0000791	.0000482
arrival_CS~3						
L1.	-.0000306	.0000335	-0.91	0.361	-.0000963	.0000351
arrival_CS~4						
L1.	.0000549	.0000972	0.56	0.573	-.0001357	.0002454
_cons	.0148449	.1105451	0.13	0.893	-.2018195	.2315092

arrival_Bi_0						
bid_c						
L1.	-1.281447	.9052736	-1.42	0.157	-3.055751	.4928562
ask_c						
L1.	1.243319	1.148388	1.08	0.279	-1.00748	3.494118
arrival_Bi_0						
L1.	.0026218	.0228112	0.11	0.908	-.0420873	.0473309
arrival_Bi_1						
L1.	.0113094	.0094652	1.19	0.232	-.0072421	.0298609
arrival_Bi_2						
L1.	.001897	.0037953	0.50	0.617	-.0055417	.0093356
arrival_Bi_3						
L1.	.0013373	.0043089	0.31	0.756	-.0071081	.0097826
arrival_Bi_4						
L1.	-.0002791	.0216807	-0.01	0.990	-.0427726	.0422143
arrival_Si_0						
L1.	.0428001	.0282248	1.52	0.129	-.0125196	.0981198
arrival_Si_1						
L1.	.0026611	.0088938	0.30	0.765	-.0147704	.0200926
arrival_Si_2						
L1.	.0032721	.0034322	0.95	0.340	-.0034549	.0099991
arrival_Si_3						
L1.	-.0040125	.0040882	-0.98	0.326	-.0120252	.0040002
arrival_Si_4						
L1.	-.0010914	.0100692	-0.11	0.914	-.0208266	.0186437
arrival_CB~0						
L1.	-.1116017	.027138	-4.11	0.000	-.1647913	-.0584121
arrival_CB~1						
L1.	.00249	.0073198	0.34	0.734	-.0118565	.0168364
arrival_CB~2						
L1.	.0061794	.0044137	1.40	0.161	-.0024713	.0148301
arrival_CB~3						
L1.	.0023247	.004978	0.47	0.641	-.0074321	.0120814
arrival_CB~4						
L1.	.0002137	.0224747	0.01	0.992	-.0438358	.0442633
arrival_CS~0						
L1.	.0193634	.033514	0.58	0.563	-.0463229	.0850496
arrival_CS~1						
L1.	.0055392	.0089738	0.62	0.537	-.0120491	.0231274
arrival_CS~2						
L1.	.0010355	.0040833	0.25	0.800	-.0069676	.0090385
arrival_CS~3						
L1.	-.0079285	.0042142	-1.88	0.060	-.0161882	.0003312
arrival_CS~4						
L1.	-.0030413	.0122283	-0.25	0.804	-.0270083	.0209257
_cons	42.26456	13.90177	3.04	0.002	15.01759	69.51154

arrival_Bi_1						
bid_c						
L1.	-.7172943	2.142913	-0.33	0.738	-4.917326	3.482737
ask_c						
L1.	2.649994	2.718399	0.97	0.330	-2.67797	7.977958
arrival_Bi_0						
L1.	.0438405	.0539973	0.81	0.417	-.0619923	.1496733
arrival_Bi_1						
L1.	.1442669	.0224056	6.44	0.000	.1003529	.188181
arrival_Bi_2						
L1.	.0357307	.008984	3.98	0.000	.0181223	.0533391
arrival_Bi_3						
L1.	.0283877	.0101998	2.78	0.005	.0083964	.048379
arrival_Bi_4						
L1.	.0031893	.0513214	0.06	0.950	-.0973988	.1037774
arrival_Si_0						
L1.	-.0605009	.0668123	-0.91	0.365	-.1914505	.0704488
arrival_Si_1						
L1.	-.0372012	.0210528	-1.77	0.077	-.078464	.0040616
arrival_Si_2						
L1.	-.0024255	.0081245	-0.30	0.765	-.0183493	.0134983
arrival_Si_3						
L1.	-.0066822	.0096773	-0.69	0.490	-.0256495	.012285
arrival_Si_4						
L1.	-.0310718	.0238351	-1.30	0.192	-.0777878	.0156442
arrival_CB~0						
L1.	.0005304	.0642396	0.01	0.993	-.1253769	.1264378
arrival_CB~1						
L1.	-.1465094	.0173269	-8.46	0.000	-.1804695	-.1125493
arrival_CB~2						
L1.	.0082924	.0104479	0.79	0.427	-.0121851	.0287698
arrival_CB~3						
L1.	.0243766	.0117837	2.07	0.039	.001281	.0474723
arrival_CB~4						
L1.	.0374903	.0532007	0.70	0.481	-.0667812	.1417619
arrival_CS~0						
L1.	-.0123364	.0793324	-0.16	0.876	-.1678252	.1431523
arrival_CS~1						
L1.	.0085998	.0212422	0.40	0.686	-.0330341	.0502338
arrival_CS~2						
L1.	-.0111895	.0096656	-1.16	0.247	-.0301338	.0077548
arrival_CS~3						
L1.	-.0045178	.0099756	-0.45	0.651	-.0240697	.015034
arrival_CS~4						
L1.	.0065094	.0289461	0.22	0.822	-.0502239	.0632427
_cons	141.8036	32.90749	4.31	0.000	77.30613	206.3011

arrival_Bi_2						
bid_c						
L1.	16.70032	6.537394	2.55	0.011	3.887262	29.51338
ask_c						
L1.	7.455813	8.293034	0.90	0.369	-8.798235	23.70986
arrival_Bi_0						
L1.	-.356261	.1647299	-2.16	0.031	-.6791258	-.0333963
arrival_Bi_1						
L1.	-.0185313	.0683527	-0.27	0.786	-.1525002	.1154376
arrival_Bi_2						
L1.	.0686636	.0274077	2.51	0.012	.0149455	.1223816
arrival_Bi_3						
L1.	-.0682767	.0311167	-2.19	0.028	-.1292644	-.0072891
arrival_Bi_4						
L1.	.0310114	.1565665	0.20	0.843	-.2758533	.3378761
arrival_Si_0						
L1.	-.0912335	.2038245	-0.45	0.654	-.4907221	.3082552
arrival_Si_1						
L1.	.0913788	.064226	1.42	0.155	-.0345018	.2172594
arrival_Si_2						
L1.	.0360822	.0247856	1.46	0.145	-.0124966	.084661
arrival_Si_3						
L1.	-.0327159	.0295227	-1.11	0.268	-.0905794	.0251476
arrival_Si_4						
L1.	.0217589	.072714	0.30	0.765	-.1207579	.1642756
arrival_CB~0						
L1.	-.2900626	.1959761	-1.48	0.139	-.6741688	.0940436
arrival_CB~1						
L1.	-.3227343	.0528593	-6.11	0.000	-.4263366	-.219132
arrival_CB~2						
L1.	-.2895938	.0318734	-9.09	0.000	-.3520644	-.2271231
arrival_CB~3						
L1.	-.0112049	.0359486	-0.31	0.755	-.0816628	.0592531
arrival_CB~4						
L1.	-.1208991	.1622998	-0.74	0.456	-.4390008	.1972026
arrival_CS~0						
L1.	.0507794	.2420199	0.21	0.834	-.4235709	.5251297
arrival_CS~1						
L1.	-.0439111	.0648037	-0.68	0.498	-.170924	.0831019
arrival_CS~2						
L1.	.0300815	.029487	1.02	0.308	-.027712	.087875
arrival_CS~3						
L1.	.0124106	.0304326	0.41	0.683	-.0472362	.0720574
arrival_CS~4						
L1.	.0299332	.088306	0.34	0.735	-.1431435	.2030098
_cons	710.6688	100.3911	7.08	0.000	513.9059	907.4317

arrival_Bi_3						
bid_c						
L1.	-6.197138	4.490052	-1.38	0.168	-14.99748	2.603201
ask_c						
L1.	13.30098	5.69587	2.34	0.020	2.137282	24.46468
arrival_Bi_0						
L1.	-.2184972	.1131408	-1.93	0.053	-.4402491	.0032546
arrival_Bi_1						
L1.	-.0700998	.0469464	-1.49	0.135	-.1621131	.0219135
arrival_Bi_2						
L1.	-.0435312	.0188243	-2.31	0.021	-.0804262	-.0066363
arrival_Bi_3						
L1.	-.0095979	.0213718	-0.45	0.653	-.0514858	.03229
arrival_Bi_4						
L1.	.1549389	.1075339	1.44	0.150	-.0558237	.3657015
arrival_Si_0						
L1.	.061668	.1399919	0.44	0.660	-.2127111	.3360471
arrival_Si_1						
L1.	-.0592845	.0441121	-1.34	0.179	-.1457426	.0271735
arrival_Si_2						
L1.	.0073241	.0170234	0.43	0.667	-.0260411	.0406893
arrival_Si_3						
L1.	.0099342	.020277	0.49	0.624	-.029808	.0496763
arrival_Si_4						
L1.	-.0198953	.0499418	-0.40	0.690	-.1177795	.0779889
arrival_CB~0						
L1.	-.2863561	.1346015	-2.13	0.033	-.5501702	-.0225421
arrival_CB~1						
L1.	-.0225841	.0363051	-0.62	0.534	-.0937409	.0485726
arrival_CB~2						
L1.	-.1002656	.0218915	-4.58	0.000	-.1431721	-.0573592
arrival_CB~3						
L1.	-.1758753	.0246904	-7.12	0.000	-.2242677	-.127483
arrival_CB~4						
L1.	-.0988995	.1114717	-0.89	0.375	-.31738	.119581
arrival_CS~0						
L1.	.2141301	.1662255	1.29	0.198	-.111666	.5399261
arrival_CS~1						
L1.	.0372628	.0445089	0.84	0.402	-.049973	.1244986
arrival_CS~2						
L1.	-.0127975	.0202525	-0.63	0.527	-.0524916	.0268966
arrival_CS~3						
L1.	-.0201052	.0209019	-0.96	0.336	-.0610722	.0208618
arrival_CS~4						
L1.	.0496357	.0606509	0.82	0.413	-.0692378	.1685092
_cons	345.3134	68.95118	5.01	0.000	210.1715	480.4552

arrival_Bi_4						
bid_c						
L1.	-1.860627	.8677346	-2.14	0.032	-3.561356	-.1598983
ask_c						
L1.	-.1023054	1.100768	-0.09	0.926	-2.25977	2.05516
arrival_Bi_0						
L1.	-.0025753	.0218653	-0.12	0.906	-.0454304	.0402798
arrival_Bi_1						
L1.	-.0068993	.0090727	-0.76	0.447	-.0246816	.0108829
arrival_Bi_2						
L1.	.0028626	.0036379	0.79	0.431	-.0042677	.0099928
arrival_Bi_3						
L1.	-.0120077	.0041302	-2.91	0.004	-.0201028	-.0039125
arrival_Bi_4						
L1.	.2190911	.0207817	10.54	0.000	.1783597	.2598225
arrival_Si_0						
L1.	.040103	.0270544	1.48	0.138	-.0129228	.0931287
arrival_Si_1						
L1.	.001627	.008525	0.19	0.849	-.0150816	.0183357
arrival_Si_2						
L1.	-.0011259	.0032899	-0.34	0.732	-.0075739	.0053222
arrival_Si_3						
L1.	-.0021357	.0039187	-0.55	0.586	-.0098162	.0055447
arrival_Si_4						
L1.	-.0014732	.0096516	-0.15	0.879	-.02039	.0174436
arrival_CB~0						
L1.	-.0076265	.0260127	-0.29	0.769	-.0586104	.0433575
arrival_CB~1						
L1.	.0015683	.0070162	0.22	0.823	-.0121832	.0153199
arrival_CB~2						
L1.	-.0049016	.0042307	-1.16	0.247	-.0131935	.0033904
arrival_CB~3						
L1.	.0073528	.0047716	1.54	0.123	-.0019994	.0167049
arrival_CB~4						
L1.	-.4567738	.0215427	-21.20	0.000	-.4989967	-.4145509
arrival_CS~0						
L1.	-.0639103	.0321243	-1.99	0.047	-.1268727	-.0009479
arrival_CS~1						
L1.	-.0081383	.0086017	-0.95	0.344	-.0249973	.0087206
arrival_CS~2						
L1.	.0007351	.0039139	0.19	0.851	-.0069361	.0084062
arrival_CS~3						
L1.	.0015453	.0040394	0.38	0.702	-.0063718	.0094625
arrival_CS~4						
L1.	-.002196	.0117212	-0.19	0.851	-.0251692	.0207772
_cons	18.41058	13.32531	1.38	0.167	-7.706541	44.52771

arrival_Si_0						
bid_c						
L1.	-.5268404	.9963975	-0.53	0.597	-2.479744	1.426063
ask_c						
L1.	-.456336	1.263983	-0.36	0.718	-2.933698	2.021026
arrival_Bi_0						
L1.	-.0023269	.0251073	-0.09	0.926	-.0515364	.0468825
arrival_Bi_1						
L1.	.0079575	.010418	0.76	0.445	-.0124613	.0283764
arrival_Bi_2						
L1.	.0260305	.0041773	6.23	0.000	.017843	.0342179
arrival_Bi_3						
L1.	.011566	.0047427	2.44	0.015	.0022705	.0208614
arrival_Bi_4						
L1.	-.0120454	.0238631	-0.50	0.614	-.0588162	.0347254
arrival_Si_0						
L1.	-.0395359	.0310659	-1.27	0.203	-.100424	.0213522
arrival_Si_1						
L1.	-.0304089	.009789	-3.11	0.002	-.049595	-.0112228
arrival_Si_2						
L1.	-.0144683	.0037777	-3.83	0.000	-.0218724	-.0070642
arrival_Si_3						
L1.	-.0150418	.0044997	-3.34	0.001	-.023861	-.0062225
arrival_Si_4						
L1.	-.0200223	.0110827	-1.81	0.071	-.041744	.0016994
arrival_CB~0						
L1.	-.0131911	.0298697	-0.44	0.659	-.0717347	.0453525
arrival_CB~1						
L1.	.0120706	.0080566	1.50	0.134	-.00372	.0278611
arrival_CB~2						
L1.	.0147719	.004858	3.04	0.002	.0052504	.0242934
arrival_CB~3						
L1.	.0176336	.0054791	3.22	0.001	.0068947	.0283724
arrival_CB~4						
L1.	-.0217343	.0247369	-0.88	0.380	-.0702178	.0267492
arrival_CS~0						
L1.	.0052782	.0368875	0.14	0.886	-.0670199	.0775764
arrival_CS~1						
L1.	-.0168499	.0098771	-1.71	0.088	-.0362086	.0025088
arrival_CS~2						
L1.	-.0325974	.0044943	-7.25	0.000	-.041406	-.0237888
arrival_CS~3						
L1.	-.0107597	.0046384	-2.32	0.020	-.0198507	-.0016686
arrival_CS~4						
L1.	-.0121132	.0134592	-0.90	0.368	-.0384927	.0142663
_cons	15.03927	15.30111	0.98	0.326	-14.95035	45.0289

arrival_Si_1						
bid_c						
L1.	-1.682026	2.492261	-0.67	0.500	-6.566769	3.202716
ask_c						
L1.	.4166517	3.161567	0.13	0.895	-5.779905	6.613209
arrival_Bi_0						
L1.	-.1358261	.0628003	-2.16	0.031	-.2589124	-.0127399
arrival_Bi_1						
L1.	.0499257	.0260582	1.92	0.055	-.0011475	.1009989
arrival_Bi_2						
L1.	.0401112	.0104487	3.84	0.000	.0196322	.0605902
arrival_Bi_3						
L1.	.0157951	.0118627	1.33	0.183	-.0074553	.0390455
arrival_Bi_4						
L1.	.2362733	.0596881	3.96	0.000	.1192868	.3532598
arrival_Si_0						
L1.	-.1764336	.0777043	-2.27	0.023	-.3287313	-.0241359
arrival_Si_1						
L1.	.0764026	.024485	3.12	0.002	.028413	.1243923
arrival_Si_2						
L1.	-.0062001	.009449	-0.66	0.512	-.0247199	.0123197
arrival_Si_3						
L1.	-.0156707	.011255	-1.39	0.164	-.0377301	.0063886
arrival_Si_4						
L1.	-.0181241	.0277209	-0.65	0.513	-.072456	.0362077
arrival_CB~0						
L1.	-.2482027	.0747123	-3.32	0.001	-.3946362	-.1017693
arrival_CB~1						
L1.	.0574206	.0201516	2.85	0.004	.0179241	.096917
arrival_CB~2						
L1.	.0273245	.0121511	2.25	0.025	.0035087	.0511403
arrival_CB~3						
L1.	.0216931	.0137047	1.58	0.113	-.0051677	.0485539
arrival_CB~4						
L1.	.2014889	.0618738	3.26	0.001	.0802185	.3227593
arrival_CS~0						
L1.	.0309953	.0922656	0.34	0.737	-.149842	.2118326
arrival_CS~1						
L1.	-.1266182	.0247052	-5.13	0.000	-.1750395	-.0781968
arrival_CS~2						
L1.	-.0299672	.0112414	-2.67	0.008	-.052	-.0079345
arrival_CS~3						
L1.	-.0323607	.0116019	-2.79	0.005	-.0551	-.0096215
arrival_CS~4						
L1.	-.0490752	.0336651	-1.46	0.145	-.1150574	.0169071
_cons	153.382	38.27225	4.01	0.000	78.36977	228.3942

arrival_Si_2						
bid_c						
L1.	1.35472	7.062215	0.19	0.848	-12.48697	15.19641
ask_c						
L1.	-6.639691	8.958797	-0.74	0.459	-24.19861	10.91923
arrival_Bi_0						
L1.	-.2748164	.1779544	-1.54	0.123	-.6236007	.0739679
arrival_Bi_1						
L1.	.3243963	.0738401	4.39	0.000	.1796724	.4691202
arrival_Bi_2						
L1.	.2049033	.029608	6.92	0.000	.1468727	.2629338
arrival_Bi_3						
L1.	.068197	.0336148	2.03	0.042	.0023133	.1340807
arrival_Bi_4						
L1.	.0600842	.1691356	0.36	0.722	-.2714156	.3915839
arrival_Si_0						
L1.	.7351668	.2201875	3.34	0.001	.3036073	1.166726
arrival_Si_1						
L1.	.3170979	.069382	4.57	0.000	.1811116	.4530842
arrival_Si_2						
L1.	-.0392741	.0267753	-1.47	0.142	-.0917528	.0132046
arrival_Si_3						
L1.	-.0487466	.0318928	-1.53	0.126	-.1112554	.0137621
arrival_Si_4						
L1.	-.0319294	.0785514	-0.41	0.684	-.1858873	.1220286
arrival_CB~0						
L1.	-.4461022	.2117091	-2.11	0.035	-.8610443	-.03116
arrival_CB~1						
L1.	.3296735	.0571028	5.77	0.000	.217754	.4415929
arrival_CB~2						
L1.	.1264044	.0344322	3.67	0.000	.0589187	.1938902
arrival_CB~3						
L1.	.1300831	.0388345	3.35	0.001	.0539688	.2061974
arrival_CB~4						
L1.	.0312397	.1753292	0.18	0.859	-.3123991	.3748786
arrival_CS~0						
L1.	.3120265	.2614492	1.19	0.233	-.2004045	.8244575
arrival_CS~1						
L1.	-.2283553	.0700061	-3.26	0.001	-.3655648	-.0911458
arrival_CS~2						
L1.	-.2064049	.0318543	-6.48	0.000	-.2688381	-.1439717
arrival_CS~3						
L1.	-.0994682	.0328757	-3.03	0.002	-.1639035	-.035033
arrival_CS~4						
L1.	-.0641632	.0953952	-0.67	0.501	-.2511344	.122808
_cons	791.1348	108.4504	7.29	0.000	578.5759	1003.694

arrival_Si_3						
bid_c						
L1.	-.5983339	6.344974	-0.09	0.925	-13.03425	11.83759
ask_c						
L1.	.4060755	8.048938	0.05	0.960	-15.36955	16.1817
arrival_Bi_0						
L1.	.1126138	.1598813	0.70	0.481	-.2007478	.4259754
arrival_Bi_1						
L1.	.0808847	.0663409	1.22	0.223	-.049141	.2109104
arrival_Bi_2						
L1.	.1197522	.026601	4.50	0.000	.0676152	.1718891
arrival_Bi_3						
L1.	.0100227	.0302008	0.33	0.740	-.0491698	.0692153
arrival_Bi_4						
L1.	.1519242	.1519581	1.00	0.317	-.1459083	.4497567
arrival_Si_0						
L1.	.2000412	.1978251	1.01	0.312	-.1876889	.5877714
arrival_Si_1						
L1.	-.0221057	.0623356	-0.35	0.723	-.1442812	.1000698
arrival_Si_2						
L1.	-.00637	.024056	-0.26	0.791	-.053519	.040779
arrival_Si_3						
L1.	-.0071596	.0286538	-0.25	0.803	-.0633199	.0490008
arrival_Si_4						
L1.	.0087237	.0705737	0.12	0.902	-.1295983	.1470456
arrival_CB~0						
L1.	.1065073	.1902078	0.56	0.576	-.2662932	.4793078
arrival_CB~1						
L1.	.1120483	.0513034	2.18	0.029	.0114954	.2126011
arrival_CB~2						
L1.	.040101	.0309352	1.30	0.195	-.0205309	.1007329
arrival_CB~3						
L1.	.0166515	.0348905	0.48	0.633	-.0517326	.0850356
arrival_CB~4						
L1.	.1360124	.1575227	0.86	0.388	-.1727264	.4447511
arrival_CS~0						
L1.	.3488563	.2348963	1.49	0.138	-.111532	.8092446
arrival_CS~1						
L1.	-.2317382	.0628963	-3.68	0.000	-.3550127	-.1084638
arrival_CS~2						
L1.	-.0668998	.0286191	-2.34	0.019	-.1229922	-.0108073
arrival_CS~3						
L1.	-.1302149	.0295369	-4.41	0.000	-.188106	-.0723237
arrival_CS~4						
L1.	-.145323	.0857068	-1.70	0.090	-.3133053	.0226593
_cons	596.2459	97.43616	6.12	0.000	405.2745	787.2173

arrival_Si_4						
bid_c						
L1.	.1089536	1.130136	0.10	0.923	-2.106073	2.32398
ask_c						
L1.	-1.308574	1.433638	-0.91	0.361	-4.118454	1.501306
arrival_Bi_0						
L1.	-.0078164	.0284773	-0.27	0.784	-.0636309	.0479981
arrival_Bi_1						
L1.	.0051373	.0118163	0.43	0.664	-.0180223	.0282968
arrival_Bi_2						
L1.	.0113379	.004738	2.39	0.017	.0020515	.0206243
arrival_Bi_3						
L1.	.0031234	.0053792	0.58	0.561	-.0074197	.0136665
arrival_Bi_4						
L1.	-.00149	.0270661	-0.06	0.956	-.0545385	.0515585
arrival_Si_0						
L1.	-.0058069	.0352357	-0.16	0.869	-.0748676	.0632537
arrival_Si_1						
L1.	.0029031	.0111029	0.26	0.794	-.0188582	.0246644
arrival_Si_2						
L1.	-.0027278	.0042847	-0.64	0.524	-.0111258	.0056701
arrival_Si_3						
L1.	-.0001729	.0051037	-0.03	0.973	-.0101759	.0098301
arrival_Si_4						
L1.	-.0050173	.0125703	-0.40	0.690	-.0296546	.0196199
arrival_CB~0						
L1.	-.006406	.0338789	-0.19	0.850	-.0728074	.0599955
arrival_CB~1						
L1.	.0075974	.0091379	0.83	0.406	-.0103126	.0255074
arrival_CB~2						
L1.	.0095554	.00551	1.73	0.083	-.0012441	.0203548
arrival_CB~3						
L1.	.0058012	.0062145	0.93	0.351	-.006379	.0179815
arrival_CB~4						
L1.	.0054623	.0280572	0.19	0.846	-.0495288	.0604534
arrival_CS~0						
L1.	-.0095668	.0418386	-0.23	0.819	-.091569	.0724353
arrival_CS~1						
L1.	.0060056	.0112028	0.54	0.592	-.0159514	.0279627
arrival_CS~2						
L1.	.0036031	.0050975	0.71	0.480	-.0063879	.013594
arrival_CS~3						
L1.	.0007843	.005261	0.15	0.881	-.009527	.0110956
arrival_CS~4						
L1.	-.0860091	.0152657	-5.63	0.000	-.1159293	-.0560889
_cons	94.50658	17.35487	5.45	0.000	60.49167	128.5215

arrival_CB~0						
bid_c						
L1.	2.818738	.9471627	2.98	0.003	.9623338	4.675143
ask_c						
L1.	.3330083	1.201526	0.28	0.782	-2.02194	2.687957
arrival_Bi_0						
L1.	.0347407	.0238667	1.46	0.145	-.0120372	.0815186
arrival_Bi_1						
L1.	.0116265	.0099032	1.17	0.240	-.0077834	.0310365
arrival_Bi_2						
L1.	.0115159	.0039709	2.90	0.004	.003733	.0192987
arrival_Bi_3						
L1.	.0103326	.0045083	2.29	0.022	.0014965	.0191687
arrival_Bi_4						
L1.	.0093325	.022684	0.41	0.681	-.0351272	.0537922
arrival_Si_0						
L1.	-.0531083	.0295309	-1.80	0.072	-.1109878	.0047711
arrival_Si_1						
L1.	-.0348514	.0093053	-3.75	0.000	-.0530895	-.0166134
arrival_Si_2						
L1.	-.0102361	.003591	-2.85	0.004	-.0172744	-.0031978
arrival_Si_3						
L1.	-.0017319	.0042774	-0.40	0.686	-.0101154	.0066516
arrival_Si_4						
L1.	.009688	.0105351	0.92	0.358	-.0109604	.0303364
arrival_CB~0						
L1.	.1474698	.0283938	5.19	0.000	.0918191	.2031206
arrival_CB~1						
L1.	.0884981	.0076585	11.56	0.000	.0734878	.1035084
arrival_CB~2						
L1.	.0037706	.0046179	0.82	0.414	-.0052804	.0128215
arrival_CB~3						
L1.	.0077773	.0052084	1.49	0.135	-.0024309	.0179855
arrival_CB~4						
L1.	.0217006	.0235146	0.92	0.356	-.0243872	.0677884
arrival_CS~0						
L1.	-.0805403	.0350648	-2.30	0.022	-.1492659	-.0118146
arrival_CS~1						
L1.	-.0275181	.009389	-2.93	0.003	-.0459202	-.009116
arrival_CS~2						
L1.	.01076	.0042722	2.52	0.012	.0023866	.0191333
arrival_CS~3						
L1.	-.0097492	.0044092	-2.21	0.027	-.0183911	-.0011074
arrival_CS~4						
L1.	-.0100289	.0127941	-0.78	0.433	-.0351049	.0150471
_cons	-15.66399	14.54504	-1.08	0.282	-44.17174	12.84376

arrival_CB~1						
bid_c						
L1.	1.533572	2.196528	0.70	0.485	-2.771544	5.838689
ask_c						
L1.	.3313231	2.786413	0.12	0.905	-5.129946	5.792593
arrival_Bi_0						
L1.	.1850618	.0553483	3.34	0.001	.076581	.2935425
arrival_Bi_1						
L1.	-.39004	.0229661	-16.98	0.000	-.4350528	-.3450272
arrival_Bi_2						
L1.	-.0271751	.0092088	-2.95	0.003	-.0452241	-.0091261
arrival_Bi_3						
L1.	.0012801	.010455	0.12	0.903	-.0192114	.0217716
arrival_Bi_4						
L1.	-.0161822	.0526055	-0.31	0.758	-.119287	.0869226
arrival_Si_0						
L1.	-.2874037	.0684839	-4.20	0.000	-.4216296	-.1531777
arrival_Si_1						
L1.	.0276739	.0215796	1.28	0.200	-.0146213	.0699691
arrival_Si_2						
L1.	-.040736	.0083278	-4.89	0.000	-.0570582	-.0244138
arrival_Si_3						
L1.	.0156099	.0099195	1.57	0.116	-.0038319	.0350517
arrival_Si_4						
L1.	.0305841	.0244315	1.25	0.211	-.0173007	.078469
arrival_CB~0						
L1.	.2893025	.0658469	4.39	0.000	.1602449	.41836
arrival_CB~1						
L1.	.0708499	.0177604	3.99	0.000	.0360401	.1056597
arrival_CB~2						
L1.	-.0122131	.0107093	-1.14	0.254	-.0332029	.0087767
arrival_CB~3						
L1.	-.0150209	.0120785	-1.24	0.214	-.0386944	.0086526
arrival_CB~4						
L1.	-.0039801	.0545318	-0.07	0.942	-.1108605	.1029003
arrival_CS~0						
L1.	-.2216211	.0813173	-2.73	0.006	-.3810001	-.062242
arrival_CS~1						
L1.	.000636	.0217737	0.03	0.977	-.0420396	.0433116
arrival_CS~2						
L1.	.0108684	.0099075	1.10	0.273	-.0085499	.0302867
arrival_CS~3						
L1.	-.013328	.0102252	-1.30	0.192	-.033369	.006713
arrival_CS~4						
L1.	-.0112037	.0296703	-0.38	0.706	-.0693565	.0469491
_cons	-119.4122	33.73084	-3.54	0.000	-185.5234	-53.30095

arrival_CB~2						
bid_c						
L1.	-4.834881	5.203716	-0.93	0.353	-15.03398	5.364215
ask_c						
L1.	-8.538351	6.601191	-1.29	0.196	-21.47645	4.399746
arrival_Bi_0						
L1.	.3748627	.1311238	2.86	0.004	.1178649	.6318606
arrival_Bi_1						
L1.	.0314993	.0544083	0.58	0.563	-.0751389	.1381375
arrival_Bi_2						
L1.	-.1759067	.0218163	-8.06	0.000	-.2186658	-.1331475
arrival_Bi_3						
L1.	-.0153089	.0247687	-0.62	0.537	-.0638546	.0332368
arrival_Bi_4						
L1.	.0258935	.1246257	0.21	0.835	-.2183685	.2701554
arrival_Si_0						
L1.	-.1359413	.1622427	-0.84	0.402	-.4539312	.1820486
arrival_Si_1						
L1.	.0155869	.0511234	0.30	0.760	-.0846132	.1157869
arrival_Si_2						
L1.	-.0136021	.0197291	-0.69	0.491	-.0522705	.0250663
arrival_Si_3						
L1.	-.0209036	.0234999	-0.89	0.374	-.0669625	.0251553
arrival_Si_4						
L1.	-.0171142	.0578798	-0.30	0.767	-.1305564	.0963281
arrival_CB~0						
L1.	.2411017	.1559955	1.55	0.122	-.0646438	.5468473
arrival_CB~1						
L1.	.0635839	.0420756	1.51	0.131	-.0188827	.1460506
arrival_CB~2						
L1.	.1642117	.025371	6.47	0.000	.1144856	.2139379
arrival_CB~3						
L1.	-.0341952	.0286148	-1.20	0.232	-.0902792	.0218888
arrival_CB~4						
L1.	.0543335	.1291894	0.42	0.674	-.198873	.30754
arrival_CS~0						
L1.	.1035788	.192646	0.54	0.591	-.2740004	.481158
arrival_CS~1						
L1.	-.016891	.0515833	-0.33	0.743	-.1179923	.0842103
arrival_CS~2						
L1.	-.0302322	.0234715	-1.29	0.198	-.0762354	.015771
arrival_CS~3						
L1.	-.0176785	.0242241	-0.73	0.466	-.0651569	.0297999
arrival_CS~4						
L1.	-.0244545	.0702909	-0.35	0.728	-.1622221	.1133132
_cons	-598.9769	79.91051	-7.50	0.000	-755.5986	-442.3552

arrival_CB~3						
bid_c						
L1.	3.933807	3.90162	1.01	0.313	-3.713228	11.58084
ask_c						
L1.	-3.388183	4.949413	-0.68	0.494	-13.08886	6.312489
arrival_Bi_0						
L1.	-.0702813	.0983134	-0.71	0.475	-.2629721	.1224094
arrival_Bi_1						
L1.	.0825116	.040794	2.02	0.043	.0025569	.1624664
arrival_Bi_2						
L1.	-.0367347	.0163573	-2.25	0.025	-.0687945	-.004675
arrival_Bi_3						
L1.	-.1663511	.0185709	-8.96	0.000	-.2027495	-.1299527
arrival_Bi_4						
L1.	-.0074295	.0934414	-0.08	0.937	-.1905711	.1757122
arrival_Si_0						
L1.	-.0762205	.1216457	-0.63	0.531	-.3146417	.1622006
arrival_Si_1						
L1.	.035358	.0383311	0.92	0.356	-.0397696	.1104855
arrival_Si_2						
L1.	-.0039988	.0147924	-0.27	0.787	-.0329914	.0249938
arrival_Si_3						
L1.	.0145253	.0176196	0.82	0.410	-.0200085	.0490592
arrival_Si_4						
L1.	.0134031	.0433968	0.31	0.757	-.0716531	.0984593
arrival_CB~0						
L1.	-.1857209	.1169617	-1.59	0.112	-.4149616	.0435197
arrival_CB~1						
L1.	.0055074	.0315473	0.17	0.861	-.0563241	.0673389
arrival_CB~2						
L1.	.0320838	.0190225	1.69	0.092	-.0051997	.0693673
arrival_CB~3						
L1.	.007835	.0214547	0.37	0.715	-.0342154	.0498854
arrival_CB~4						
L1.	.2706641	.0968631	2.79	0.005	.080816	.4605123
arrival_CS~0						
L1.	-.1383797	.1444413	-0.96	0.338	-.4214794	.1447201
arrival_CS~1						
L1.	.0054009	.0386759	0.14	0.889	-.0704024	.0812042
arrival_CS~2						
L1.	.0025067	.0175983	0.14	0.887	-.0319854	.0369988
arrival_CS~3						
L1.	-.0048086	.0181627	-0.26	0.791	-.0404068	.0307895
arrival_CS~4						
L1.	-.0363587	.0527024	-0.69	0.490	-.1396536	.0669361
_cons	-410.4645	59.91497	-6.85	0.000	-527.8957	-293.0333

arrival_CB~4						
bid_c						
L1.	2.562799	.913772	2.80	0.005	.7718389	4.353759
ask_c						
L1.	-2.113926	1.159169	-1.82	0.068	-4.385854	.1580028
arrival_Bi_0						
L1.	.0070724	.0230253	0.31	0.759	-.0380564	.0522012
arrival_Bi_1						
L1.	.0075126	.0095541	0.79	0.432	-.011213	.0262383
arrival_Bi_2						
L1.	-.0034188	.0038309	-0.89	0.372	-.0109273	.0040897
arrival_Bi_3						
L1.	.0305063	.0043494	7.01	0.000	.0219817	.0390309
arrival_Bi_4						
L1.	-.3467406	.0218843	-15.84	0.000	-.389633	-.3038482
arrival_Si_0						
L1.	-.0030268	.0284898	-0.11	0.915	-.0588658	.0528122
arrival_Si_1						
L1.	.0067707	.0089773	0.75	0.451	-.0108244	.0243658
arrival_Si_2						
L1.	.0007231	.0034644	0.21	0.835	-.0060671	.0075132
arrival_Si_3						
L1.	.0011472	.0041266	0.28	0.781	-.0069407	.0092352
arrival_Si_4						
L1.	.0036682	.0101637	0.36	0.718	-.0162523	.0235886
arrival_CB~0						
L1.	.0179953	.0273928	0.66	0.511	-.0356936	.0716842
arrival_CB~1						
L1.	.0038008	.0073885	0.51	0.607	-.0106803	.0182819
arrival_CB~2						
L1.	.010687	.0044551	2.40	0.016	.0019551	.0194189
arrival_CB~3						
L1.	-.0143619	.0050248	-2.86	0.004	-.0242103	-.0045136
arrival_CB~4						
L1.	.2276926	.0226856	10.04	0.000	.1832295	.2721556
arrival_CS~0						
L1.	-.0386324	.0338286	-1.14	0.253	-.1049353	.0276705
arrival_CS~1						
L1.	-.0031437	.009058	-0.35	0.729	-.0208971	.0146097
arrival_CS~2						
L1.	.003176	.0041216	0.77	0.441	-.0049021	.0112542
arrival_CS~3						
L1.	.0001574	.0042538	0.04	0.970	-.0081798	.0084946
arrival_CS~4						
L1.	.0014727	.0123431	0.12	0.905	-.0227193	.0256647
_cons	-31.46873	14.03228	-2.24	0.025	-58.97149	-3.965972

arrival_CS~0						
bid_c						
L1.	-.2092607	.8274182	-0.25	0.800	-1.830971	1.412449
ask_c						
L1.	-1.128524	1.049624	-1.08	0.282	-3.18575	.9287013
arrival_Bi_0						
L1.	.0160465	.0208494	0.77	0.442	-.0248175	.0569105
arrival_Bi_1						
L1.	-.0250994	.0086512	-2.90	0.004	-.0420554	-.0081433
arrival_Bi_2						
L1.	-.0027628	.0034689	-0.80	0.426	-.0095617	.0040362
arrival_Bi_3						
L1.	-.0060924	.0039383	-1.55	0.122	-.0138114	.0016266
arrival_Bi_4						
L1.	-.0019645	.0198161	-0.10	0.921	-.0408034	.0368744
arrival_Si_0						
L1.	-.4605128	.0257974	-17.85	0.000	-.5110749	-.4099508
arrival_Si_1						
L1.	-.0067122	.0081289	-0.83	0.409	-.0226445	.0092201
arrival_Si_2						
L1.	.0014111	.003137	0.45	0.653	-.0047374	.0075596
arrival_Si_3						
L1.	.0035193	.0037366	0.94	0.346	-.0038043	.0108429
arrival_Si_4						
L1.	.003213	.0092032	0.35	0.727	-.0148249	.0212509
arrival_CB~0						
L1.	.0255745	.0248041	1.03	0.303	-.0230406	.0741897
arrival_CB~1						
L1.	-.0210481	.0066902	-3.15	0.002	-.0341607	-.0079354
arrival_CB~2						
L1.	-.002158	.0040341	-0.53	0.593	-.0100648	.0057487
arrival_CB~3						
L1.	-.007468	.0045499	-1.64	0.101	-.0163857	.0014496
arrival_CB~4						
L1.	-.0044125	.0205418	-0.21	0.830	-.0446736	.0358487
arrival_CS~0						
L1.	-.2178236	.0306317	-7.11	0.000	-.2778607	-.1577865
arrival_CS~1						
L1.	.0124765	.008202	1.52	0.128	-.0035991	.0285521
arrival_CS~2						
L1.	.004092	.0037321	1.10	0.273	-.0032228	.0114067
arrival_CS~3						
L1.	-.0038799	.0038518	-1.01	0.314	-.0114292	.0036694
arrival_CS~4						
L1.	.0011338	.0111766	0.10	0.919	-.020772	.0230395
_cons	-40.92614	12.70619	-3.22	0.001	-65.82982	-16.02246

arrival_CS~1						
bid_c						
L1.	4.407038	2.835363	1.55	0.120	-1.150171	9.964247
ask_c						
L1.	-5.258833	3.596809	-1.46	0.144	-12.30845	1.790783
arrival_Bi_0						
L1.	.111238	.0714458	1.56	0.119	-.0287931	.2512692
arrival_Bi_1						
L1.	-.0109166	.0296456	-0.37	0.713	-.0690209	.0471876
arrival_Bi_2						
L1.	-.0074937	.0118871	-0.63	0.528	-.030792	.0158046
arrival_Bi_3						
L1.	.0115873	.0134958	0.86	0.391	-.0148639	.0380385
arrival_Bi_4						
L1.	.0064932	.0679052	0.10	0.924	-.1265985	.1395848
arrival_Si_0						
L1.	.0629397	.0884016	0.71	0.476	-.1103244	.2362037
arrival_Si_1						
L1.	-.5221765	.0278557	-18.75	0.000	-.5767728	-.4675803
arrival_Si_2						
L1.	.0122222	.0107499	1.14	0.256	-.0088471	.0332916
arrival_Si_3						
L1.	-.0312109	.0128044	-2.44	0.015	-.0563072	-.0061147
arrival_Si_4						
L1.	.0057761	.0315371	0.18	0.855	-.0560355	.0675877
arrival_CB~0						
L1.	.1097528	.0849977	1.29	0.197	-.0568396	.2763452
arrival_CB~1						
L1.	-.1037194	.0229258	-4.52	0.000	-.1486532	-.0587855
arrival_CB~2						
L1.	.0233621	.0138239	1.69	0.091	-.0037323	.0504565
arrival_CB~3						
L1.	.0179966	.0155914	1.15	0.248	-.012562	.0485552
arrival_CB~4						
L1.	-.0237861	.0703918	-0.34	0.735	-.1617514	.1141792
arrival_CS~0						
L1.	.0345366	.1049675	0.33	0.742	-.171196	.2402692
arrival_CS~1						
L1.	.1187098	.0281063	4.22	0.000	.0636224	.1737971
arrival_CS~2						
L1.	.0051705	.012789	0.40	0.686	-.0198954	.0302364
arrival_CS~3						
L1.	-.0446566	.0131991	-3.38	0.001	-.0705263	-.018787
arrival_CS~4						
L1.	-.015739	.0382996	-0.41	0.681	-.0908049	.0593268
_cons	-211.9145	43.54106	-4.87	0.000	-297.2534	-126.5756

arrival_CS~2						
bid_c						
L1.	2.358627	6.272515	0.38	0.707	-9.935276	14.65253
ask_c						
L1.	-.1490543	7.95702	-0.02	0.985	-15.74453	15.44642
arrival_Bi_0						
L1.	.1947063	.1580555	1.23	0.218	-.1150767	.5044894
arrival_Bi_1						
L1.	-.0847639	.0655832	-1.29	0.196	-.2133047	.0437769
arrival_Bi_2						
L1.	-.1003526	.0262972	-3.82	0.000	-.1518942	-.0488111
arrival_Bi_3						
L1.	-.0073183	.0298559	-0.25	0.806	-.0658349	.0511982
arrival_Bi_4						
L1.	.0809401	.1502228	0.54	0.590	-.2134912	.3753714
arrival_Si_0						
L1.	.2660277	.195566	1.36	0.174	-.1172746	.64933
arrival_Si_1						
L1.	-.0802895	.0616237	-1.30	0.193	-.2010697	.0404908
arrival_Si_2						
L1.	-.0587126	.0237813	-2.47	0.014	-.1053231	-.0121021
arrival_Si_3						
L1.	.0085601	.0283265	0.30	0.763	-.0469589	.0640791
arrival_Si_4						
L1.	.0205389	.0697678	0.29	0.768	-.1162034	.1572812
arrival_CB~0						
L1.	.4238049	.1880357	2.25	0.024	.0552618	.792348
arrival_CB~1						
L1.	-.1417778	.0507175	-2.80	0.005	-.2411824	-.0423733
arrival_CB~2						
L1.	-.0550356	.0305819	-1.80	0.072	-.1149751	.0049039
arrival_CB~3						
L1.	.0032229	.034492	0.09	0.926	-.0643802	.0708261
arrival_CB~4						
L1.	.0431356	.1557238	0.28	0.782	-.2620774	.3483486
arrival_CS~0						
L1.	.2993727	.2322138	1.29	0.197	-.155758	.7545034
arrival_CS~1						
L1.	.0474401	.062178	0.76	0.445	-.0744266	.1693068
arrival_CS~2						
L1.	.0831653	.0282923	2.94	0.003	.0277134	.1386172
arrival_CS~3						
L1.	.0908057	.0291995	3.11	0.002	.0335756	.1480357
arrival_CS~4						
L1.	-.0353449	.0847281	-0.42	0.677	-.2014089	.1307191
_cons	-777.4303	96.32345	-8.07	0.000	-966.2208	-588.6398

arrival_CS~3						
bid_c						
L1.	-7.304984	5.344681	-1.37	0.172	-17.78037	3.170397
ask_c						
L1.	8.810524	6.780013	1.30	0.194	-4.478057	22.09911
arrival_Bi_0						
L1.	-.0213768	.1346758	-0.16	0.874	-.2853366	.242583
arrival_Bi_1						
L1.	-.0711906	.0558821	-1.27	0.203	-.1807176	.0383363
arrival_Bi_2						
L1.	-.0623202	.0224073	-2.78	0.005	-.1062377	-.0184027
arrival_Bi_3						
L1.	.0337784	.0254396	1.33	0.184	-.0160823	.0836392
arrival_Bi_4						
L1.	-.0164807	.1280018	-0.13	0.898	-.2673595	.2343981
arrival_Si_0						
L1.	.1571861	.1666378	0.94	0.346	-.1694179	.4837901
arrival_Si_1						
L1.	.0197519	.0525083	0.38	0.707	-.0831625	.1226662
arrival_Si_2						
L1.	-.0720136	.0202636	-3.55	0.000	-.1117295	-.0322978
arrival_Si_3						
L1.	-.147203	.0241365	-6.10	0.000	-.1945096	-.0998964
arrival_Si_4						
L1.	-.1561281	.0594477	-2.63	0.009	-.2726434	-.0396128
arrival_CB~0						
L1.	.042134	.1602213	0.26	0.793	-.2718941	.356162
arrival_CB~1						
L1.	-.0574334	.0432154	-1.33	0.184	-.142134	.0272672
arrival_CB~2						
L1.	.0034343	.0260582	0.13	0.895	-.0476389	.0545075
arrival_CB~3						
L1.	.0177184	.02939	0.60	0.547	-.0398848	.0753217
arrival_CB~4						
L1.	-.0487831	.132689	-0.37	0.713	-.3088489	.2112826
arrival_CS~0						
L1.	-.3223697	.1978646	-1.63	0.103	-.7101773	.0654378
arrival_CS~1						
L1.	-.0018426	.0529806	-0.03	0.972	-.1056827	.1019975
arrival_CS~2						
L1.	.0009477	.0241073	0.04	0.969	-.0463017	.0481971
arrival_CS~3						
L1.	.0411053	.0248803	1.65	0.099	-.0076593	.0898698
arrival_CS~4						
L1.	-.0599016	.0721951	-0.83	0.407	-.2014013	.0815981
_cons	-418.2385	82.07523	-5.10	0.000	-579.103	-257.374

arrival_CS~4						
bid_c						
L1.	.1713749	1.593713	0.11	0.914	-2.952245	3.294995
ask_c						
L1.	-1.059406	2.02171	-0.52	0.600	-5.021885	2.903073
arrival_Bi_0						
L1.	.0335793	.0401585	0.84	0.403	-.04513	.1122886
arrival_Bi_1						
L1.	-.0081703	.0166633	-0.49	0.624	-.0408298	.0244892
arrival_Bi_2						
L1.	-.0262262	.0066816	-3.93	0.000	-.0393218	-.0131305
arrival_Bi_3						
L1.	-.0098854	.0075858	-1.30	0.193	-.0247532	.0049825
arrival_Bi_4						
L1.	-.0087428	.0381684	-0.23	0.819	-.0835515	.0660659
arrival_Si_0						
L1.	.0321517	.0496892	0.65	0.518	-.0652373	.1295407
arrival_Si_1						
L1.	.021461	.0156573	1.37	0.170	-.0092267	.0521487
arrival_Si_2						
L1.	.0007731	.0060423	0.13	0.898	-.0110697	.0126158
arrival_Si_3						
L1.	.0080914	.0071972	1.12	0.261	-.0060148	.0221976
arrival_Si_4						
L1.	-.4475799	.0177265	-25.25	0.000	-.4823232	-.4128366
arrival_CB~0						
L1.	.0428923	.0477759	0.90	0.369	-.0507467	.1365313
arrival_CB~1						
L1.	.0170592	.0128863	1.32	0.186	-.0081974	.0423158
arrival_CB~2						
L1.	-.0049689	.0077702	-0.64	0.523	-.0201982	.0102605
arrival_CB~3						
L1.	-.0158358	.0087637	-1.81	0.071	-.0330124	.0013407
arrival_CB~4						
L1.	-.0090907	.0395661	-0.23	0.818	-.0866389	.0684574
arrival_CS~0						
L1.	.0031288	.0590006	0.05	0.958	-.1125103	.1187679
arrival_CS~1						
L1.	-.0024167	.0157981	-0.15	0.878	-.0333804	.0285471
arrival_CS~2						
L1.	.0100224	.0071885	1.39	0.163	-.0040668	.0241115
arrival_CS~3						
L1.	.0014983	.007419	0.20	0.840	-.0130426	.0160393
arrival_CS~4						
L1.	-.0090387	.0215276	-0.42	0.675	-.051232	.0331546
_cons	-21.09391	24.47375	-0.86	0.389	-69.06157	26.87375

APPENDIX B: Results for regression (III)

Because of space limitations, two sample regressions are provided for each security in the sample data

Sampo 25th November (t=150ms)

Source	SS	df	MS
Model	9.2439e-07	12	7.7032e-08
Residual	.000073184	5665	1.2919e-08
Total	.000074109	5677	1.3054e-08

Number of obs =	5678
F(12, 5665) =	5.96
Prob > F =	0.0000
R-squared =	0.0125
Adj R-squared =	0.0104
Root MSE =	.00011

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	7.68e-08	2.44e-08	3.15	0.002	2.90e-08	1.25e-07
arrival_Bi_1	7.73e-09	7.01e-09	1.10	0.270	-6.01e-09	2.15e-08
arrival_Bi_2	-3.63e-09	4.39e-09	-0.83	0.408	-1.22e-08	4.98e-09
arrival_Bi_3	2.45e-08	6.38e-09	3.84	0.000	1.20e-08	3.70e-08
arrival_Bi_4	-3.05e-08	1.31e-08	-2.32	0.020	-5.63e-08	-4.78e-09
arrival_Bi_5	-3.16e-08	1.38e-08	-2.30	0.022	-5.86e-08	-4.62e-09
arrival_Si_0	-6.18e-08	1.88e-08	-3.29	0.001	-9.87e-08	-2.50e-08
arrival_Si_1	-8.84e-09	5.99e-09	-1.47	0.140	-2.06e-08	2.91e-09
arrival_Si_2	1.30e-09	4.16e-09	0.31	0.755	-6.86e-09	9.45e-09
arrival_Si_3	2.93e-09	5.53e-09	0.53	0.596	-7.92e-09	1.38e-08
arrival_Si_4	4.61e-09	1.47e-08	0.31	0.753	-2.41e-08	3.33e-08
arrival_Si_5	8.81e-08	2.07e-08	4.25	0.000	4.75e-08	1.29e-07
_cons	1.64e-06	1.88e-06	0.87	0.382	-2.04e-06	5.32e-06

Sampo 25th November (t=150ms)

Source	SS	df	MS
Model	9.2439e-07	12	7.7032e-08
Residual	.000073184	5665	1.2919e-08
Total	.000074109	5677	1.3054e-08

Number of obs =	5678
F(12, 5665) =	5.96
Prob > F =	0.0000
R-squared =	0.0125
Adj R-squared =	0.0104
Root MSE =	.00011

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	7.68e-08	2.44e-08	3.15	0.002	2.90e-08	1.25e-07
arrival_Bi_1	7.73e-09	7.01e-09	1.10	0.270	-6.01e-09	2.15e-08
arrival_Bi_2	-3.63e-09	4.39e-09	-0.83	0.408	-1.22e-08	4.98e-09
arrival_Bi_3	2.45e-08	6.38e-09	3.84	0.000	1.20e-08	3.70e-08
arrival_Bi_4	-3.05e-08	1.31e-08	-2.32	0.020	-5.63e-08	-4.78e-09
arrival_Bi_5	-3.16e-08	1.38e-08	-2.30	0.022	-5.86e-08	-4.62e-09
arrival_Si_0	-6.18e-08	1.88e-08	-3.29	0.001	-9.87e-08	-2.50e-08
arrival_Si_1	-8.84e-09	5.99e-09	-1.47	0.140	-2.06e-08	2.91e-09
arrival_Si_2	1.30e-09	4.16e-09	0.31	0.755	-6.86e-09	9.45e-09
arrival_Si_3	2.93e-09	5.53e-09	0.53	0.596	-7.92e-09	1.38e-08
arrival_Si_4	4.61e-09	1.47e-08	0.31	0.753	-2.41e-08	3.33e-08
arrival_Si_5	8.81e-08	2.07e-08	4.25	0.000	4.75e-08	1.29e-07
_cons	1.64e-06	1.88e-06	0.87	0.382	-2.04e-06	5.32e-06

Fortum 22nd November (t=150ms)

Source	SS	df	MS
Model	6.3922e-07	12	5.3268e-08
Residual	.000088473	6599	1.3407e-08
Total	.000089112	6611	1.3479e-08

Number of obs	=	6612
F(12, 6599)	=	3.97
Prob > F	=	0.0000
R-squared	=	0.0072
Adj R-squared	=	0.0054
Root MSE	=	.00012

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	3.02e-08	2.08e-08	1.45	0.147	-1.06e-08	7.09e-08
arrival_Bi_1	2.62e-08	7.86e-09	3.34	0.001	1.08e-08	4.16e-08
arrival_Bi_2	2.11e-09	3.79e-09	0.56	0.579	-5.33e-09	9.54e-09
arrival_Bi_3	-3.47e-09	3.99e-09	-0.87	0.384	-1.13e-08	4.35e-09
arrival_Bi_4	-1.04e-08	9.28e-09	-1.13	0.260	-2.86e-08	7.74e-09
arrival_Bi_5	-9.19e-08	4.86e-08	-1.89	0.059	-1.87e-07	3.35e-09
arrival_Si_0	-4.02e-08	2.01e-08	-1.99	0.046	-7.96e-08	-6.71e-10
arrival_Si_1	-1.97e-08	6.86e-09	-2.87	0.004	-3.32e-08	-6.27e-09
arrival_Si_2	-3.93e-09	2.89e-09	-1.36	0.174	-9.59e-09	1.73e-09
arrival_Si_3	9.42e-09	3.97e-09	2.37	0.018	1.63e-09	1.72e-08
arrival_Si_4	-1.14e-08	1.27e-08	-0.89	0.372	-3.63e-08	1.36e-08
arrival_Si_5	2.54e-07	9.15e-08	2.78	0.005	7.52e-08	4.34e-07
_cons	-3.16e-07	1.81e-06	-0.17	0.862	-3.87e-06	3.24e-06

Fortum 25th November (t=150ms)

Source	SS	df	MS
Model	7.5832e-07	12	6.3193e-08
Residual	.000060368	3681	1.6400e-08
Total	.000061126	3693	1.6552e-08

Number of obs	=	3694
F(12, 3681)	=	3.85
Prob > F	=	0.0000
R-squared	=	0.0124
Adj R-squared	=	0.0092
Root MSE	=	.00013

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	4.44e-08	1.32e-08	3.37	0.001	1.86e-08	7.03e-08
arrival_Bi_1	1.70e-08	1.26e-08	1.35	0.178	-7.76e-09	4.18e-08
arrival_Bi_2	-2.82e-09	4.94e-09	-0.57	0.568	-1.25e-08	6.87e-09
arrival_Bi_3	-9.18e-09	8.67e-09	-1.06	0.290	-2.62e-08	7.81e-09
arrival_Bi_4	1.89e-08	5.22e-08	0.36	0.717	-8.35e-08	1.21e-07
arrival_Bi_5	-1.23e-08	1.81e-07	-0.07	0.946	-3.68e-07	3.43e-07
arrival_Si_0	-8.62e-08	1.96e-08	-4.40	0.000	-1.25e-07	-4.78e-08
arrival_Si_1	8.87e-09	1.14e-08	0.78	0.437	-1.35e-08	3.12e-08
arrival_Si_2	4.81e-09	4.51e-09	1.07	0.287	-4.03e-09	1.36e-08
arrival_Si_3	2.26e-09	7.44e-09	0.30	0.761	-1.23e-08	1.68e-08
arrival_Si_4	3.79e-09	4.37e-08	0.09	0.931	-8.19e-08	8.95e-08
arrival_Si_5	3.60e-07	1.11e-07	3.25	0.001	1.43e-07	5.77e-07
_cons	2.58e-06	2.61e-06	0.99	0.323	-2.54e-06	7.69e-06

UPM 24th November (t=150ms)

Source	SS	df	MS
Model	2.6400e-06	12	2.2000e-07
Residual	.00027182	7552	3.5993e-08
Total	.00027446	7564	3.6285e-08

Number of obs =	7565
F(12, 7552) =	6.11
Prob > F =	0.0000
R-squared =	0.0096
Adj R-squared =	0.0080
Root MSE =	.00019

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	4.81e-08	2.78e-08	1.73	0.083	-6.34e-09	1.03e-07
arrival_Bi_1	1.46e-08	5.45e-09	2.68	0.007	3.93e-09	2.53e-08
arrival_Bi_2	5.57e-09	3.21e-09	1.73	0.083	-7.27e-10	1.19e-08
arrival_Bi_3	-6.47e-09	5.62e-09	-1.15	0.250	-1.75e-08	4.55e-09
arrival_Bi_4	-4.90e-08	1.09e-08	-4.51	0.000	-7.03e-08	-2.77e-08
arrival_Bi_5	3.98e-09	2.42e-08	0.16	0.869	-4.34e-08	5.13e-08
arrival_Si_0	-1.26e-07	3.07e-08	-4.12	0.000	-1.87e-07	-6.62e-08
arrival_Si_1	-6.69e-09	6.37e-09	-1.05	0.294	-1.92e-08	5.80e-09
arrival_Si_2	-5.83e-09	2.72e-09	-2.14	0.032	-1.12e-08	-4.95e-10
arrival_Si_3	1.56e-09	5.09e-09	0.31	0.759	-8.41e-09	1.15e-08
arrival_Si_4	2.82e-08	8.78e-09	3.22	0.001	1.10e-08	4.54e-08
arrival_Si_5	1.83e-08	1.82e-08	1.01	0.314	-1.73e-08	5.39e-08
_cons	3.58e-07	2.64e-06	0.14	0.892	-4.82e-06	5.54e-06

UPM 26th November (t=150ms)

Source	SS	df	MS
Model	1.0431e-06	12	8.6924e-08
Residual	.000232142	5971	3.8878e-08
Total	.000233185	5983	3.8975e-08

Number of obs =	5984
F(12, 5971) =	2.24
Prob > F =	0.0083
R-squared =	0.0045
Adj R-squared =	0.0025
Root MSE =	.0002

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	2.29e-09	3.35e-08	0.07	0.946	-6.34e-08	6.80e-08
arrival_Bi_1	1.96e-08	6.21e-09	3.16	0.002	7.43e-09	3.18e-08
arrival_Bi_2	2.44e-09	3.04e-09	0.80	0.422	-3.52e-09	8.39e-09
arrival_Bi_3	1.20e-09	5.86e-09	0.21	0.838	-1.03e-08	1.27e-08
arrival_Bi_4	-2.78e-08	3.17e-08	-0.88	0.380	-9.01e-08	3.44e-08
arrival_Bi_5	-1.33e-07	8.64e-08	-1.53	0.125	-3.02e-07	3.68e-08
arrival_Si_0	1.93e-08	3.31e-08	0.58	0.560	-4.56e-08	8.42e-08
arrival_Si_1	-1.63e-08	5.82e-09	-2.81	0.005	-2.78e-08	-4.93e-09
arrival_Si_2	2.08e-09	3.16e-09	0.66	0.510	-4.11e-09	8.27e-09
arrival_Si_3	8.38e-10	4.18e-09	0.20	0.841	-7.36e-09	9.04e-09
arrival_Si_4	1.47e-08	2.86e-08	0.51	0.608	-4.14e-08	7.07e-08
arrival_Si_5	-8.00e-09	3.36e-08	-0.24	0.812	-7.38e-08	5.78e-08
_cons	-2.49e-06	3.13e-06	-0.79	0.427	-8.63e-06	3.66e-06

Stora Enso 24th November (t=80ms)

Source	SS	df	MS
Model	1.5287e-06	12	1.2739e-07
Residual	.000381186	15908	2.3962e-08
Total	.000382715	15920	2.4040e-08

Number of obs	=	15921
F(12, 15908)	=	5.32
Prob > F	=	0.0000
R-squared	=	0.0040
Adj R-squared	=	0.0032
Root MSE	=	.00015

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	7.26e-09	3.25e-09	2.24	0.025	8.95e-10	1.36e-08
arrival_Bi_1	2.54e-09	1.35e-09	1.88	0.060	-1.06e-10	5.18e-09
arrival_Bi_2	-7.47e-10	6.00e-10	-1.25	0.213	-1.92e-09	4.29e-10
arrival_Bi_3	-7.75e-10	4.19e-10	-1.85	0.064	-1.60e-09	4.62e-11
arrival_Bi_4	-6.50e-10	5.35e-10	-1.22	0.224	-1.70e-09	3.98e-10
arrival_Bi_5	-2.28e-09	1.93e-09	-1.18	0.237	-6.06e-09	1.50e-09
arrival_Si_0	-9.85e-09	7.82e-09	-1.26	0.208	-2.52e-08	5.49e-09
arrival_Si_1	-1.10e-08	1.86e-09	-5.95	0.000	-1.47e-08	-7.41e-09
arrival_Si_2	-9.76e-10	5.49e-10	-1.78	0.076	-2.05e-09	1.01e-10
arrival_Si_3	2.15e-10	3.66e-10	0.59	0.558	-5.03e-10	9.33e-10
arrival_Si_4	-5.35e-10	6.55e-10	-0.82	0.414	-1.82e-09	7.49e-10
arrival_Si_5	6.17e-10	1.39e-09	0.45	0.656	-2.10e-09	3.33e-09
_cons	2.42e-06	1.38e-06	1.75	0.080	-2.90e-07	5.13e-06

Stora Enso 25th November (t=80ms)

Source	SS	df	MS
Model	1.4310e-06	12	1.1925e-07
Residual	.000237595	10260	2.3157e-08
Total	.000239026	10272	2.3270e-08

Number of obs	=	10273
F(12, 10260)	=	5.15
Prob > F	=	0.0000
R-squared	=	0.0060
Adj R-squared	=	0.0048
Root MSE	=	.00015

p_change_l~d	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
arrival_Bi_0	-5.24e-10	6.56e-09	-0.08	0.936	-1.34e-08	1.23e-08
arrival_Bi_1	4.55e-09	1.93e-09	2.36	0.018	7.74e-10	8.33e-09
arrival_Bi_2	-1.08e-09	6.84e-10	-1.58	0.114	-2.42e-09	2.59e-10
arrival_Bi_3	-1.81e-10	5.87e-10	-0.31	0.758	-1.33e-09	9.69e-10
arrival_Bi_4	2.81e-09	9.99e-10	2.82	0.005	8.55e-10	4.77e-09
arrival_Bi_5	-7.43e-10	1.93e-09	-0.39	0.700	-4.53e-09	3.04e-09
arrival_Si_0	-8.72e-09	5.22e-09	-1.67	0.095	-1.89e-08	1.51e-09
arrival_Si_1	-1.51e-09	1.84e-09	-0.82	0.411	-5.12e-09	2.10e-09
arrival_Si_2	-1.58e-09	6.99e-10	-2.26	0.024	-2.95e-09	-2.09e-10
arrival_Si_3	-6.61e-10	5.30e-10	-1.25	0.212	-1.70e-09	3.77e-10
arrival_Si_4	2.33e-09	8.93e-10	2.61	0.009	5.79e-10	4.08e-09
arrival_Si_5	6.34e-09	1.42e-09	4.47	0.000	3.56e-09	9.12e-09
_cons	3.78e-07	1.72e-06	0.22	0.826	-2.99e-06	3.74e-06