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Master's Thesis

Trading Cost Analysis: Implementation Shortfall and Price Reversion of Institutional Orders in OMXH25 Stocks

Supervisor: Professor Mikael Collan

Examiner: Postdoctoral researcher Jan Stoklasa

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ABSTRACT

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The purpose of this thesis is to conduct a transaction cost analysis (TCA) of stock trade order executions for a Finnish Asset Management company. Specifically, the purpose is to analyze whether liquidity or market volatility conditions affect the two key components of TCA: Implementation shortfall (slippage) and post-execution price reversion. Additionally, the changes in market infrastructure and regulations are discussed.

The empirical analysis focuses on finding out whether stock liquidity and market volatility affect the implementation shortfall and price reversion of algorithmic trade order executions. The analysis is done for OMXH25 trade order executions and it is analyzed on a parent order level data.

Stock markets have been through significant changes the past few years. Institutional investors especially have raised concerns of executing trades with high-frequency trading (HFT) counterparties. With the increasing demand for anonymity and changes in regulations, stock markets are now fragmented and investors can trade away from displayed markets and execute orders in dark pools instead. Speed and use of algorithms now play a vital role in determining the realized execution price in trading. As the financial markets have become more complex and opaque, the importance of proper pre-trade and post-trade transaction cost analysis is increasing.

TIIVISTELMÄ

Kirjoittaja:	Joni Siltanen
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Tämän tutkimuksen tarkoituksena on tehdä analyysi arvopaperikaupan kustannuksista (TCA-analyysi) osakekauppojen osalta suomalaiselle varainhoitoyritykselle. Erityisesti tarkoituksena on tutkia, vaikuttaako osakkeen likviditeetti tai markkinoiden volatiliteetti kahteen TCA-analyysin merkittävään komponenttiin: toimeenpanon toteutuksen vajeeseen sekä toteutuksen jälkeiseen hintatrendiin. Tämän lisäksi käydään läpi merkittäviä muutoksia osakemarkkinoiden infrastruktuurissa sekä säännöstelyssä.

Tutkimuksen empiirisen analyysin tarkoituksena on selvittää, vaikuttaako osakkeen likviditeetti ja markkinoiden volatiliteetti toimeenpanon toteutukseen sekä toteutuksen jälkeiseen hintatrendiin. Analyysi on toteutettu suomalaisille OMXH25 osakkeille, joiden kaupankäynnin toteutuksessa on käytetty algoritmeihin perustuvaa menetelmää. Analyysi on toteutettu toimeksiannon isäntätasolla.

Osakemarkkinoilla on tapahtunut viime vuosien aikana merkittäviä muutoksia. Erityisesti institutionaaliset sijoittajat ovat huolisaan kaupankäynnistä niinkutsuttujen HFT-osapuolien kanssa. Anonyymin kaupankäynnin kysynnän kasvaessa sekä säännösten muuttumisen johdosta osakemarkkinat ovat nykyään pirstaloituneet ja sijoittajilla on mahdollisuus käydä kauppaa dark pooleissa näkyvien markkinoiden ulkopuolella. Nopeus ja kaupankäyntialgoritmien käyttö ovat nyt merkittäviä ajureita toteutuneen kaupankäyntihinnan muodostumisessa. Kun osakemarkkinat ovat muuttuneet entistä monimutkaisemmiksi, arvopaperikaupan kustannusanalyysin merkitys institutionaalisille sijoittajille on kasvussa.

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The process of writing this thesis has been a rewarding experience, although more time consuming and challenging than I had anticipated. I found the topic highly interesting and I cannot recall how many times I got lost reading about topics more or less related to this one. Therefore, I would like to thank Antti, the contact at the Finnish Asset Management company, for allowing me to write my thesis using their data and for all his insights and ideas. In writing my thesis, I faced numerous difficulties and I want to thank my supervisor Professor Mikael Collan for his support and guidance throughout this process.

Above everything else, I want to thank my family and friends for all their support. Without you, I could not have done it. And in case I forgot about my thesis, you made sure to remind me by constantly asking "how is your thesis going?" every time for the past year or so. I especially want to thank my dad for he has been a huge help through all these years.

This journey began in Lappeenranta University of Technology in fall 2011. Back then, I had no idea what to expect going into the first lectures. Now, five and a half years later, as I reflect back to my times in Lappeenranta and semester abroad in San Diego, I cannot believe how lucky I have been. Those were the best times of my life and it is all thanks to the amazing friends I have made.

For all the work I have put into this thesis, it feels incredibly satisfying to write these last words. And now, finally, when I am asked "how is your thesis going?" I can finally answer: It is done.

15.1.2017

Helsinki

Joni Siltanen

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Abbreviations

ADV	Average Daily Volume
AT	Algorithmic Trading
EBBO	European Best Bid and Offer price
ECN	Electronic Communication Network
ETF	Exchange-Traded Fund
HFT	High-Frequency Trading
IFS	Intelligent Financial Systems
IOC	Immediate Or Cancel (trade order type)
IS	Implementation Shortfall (also known as Slippage)
MiFID	Markets in Financial Instruments Directive
MTF	Multilateral Trading Facility
NBBO	National Best Bid and Offer price (U.S. equivalent to EBBO)
SOR	Smart Order Router
TCA	Transaction Cost Analysis (also known as Trading Cost Analysis)
VWAP	Volume-Weighted Average trade Price

1. Introduction

1.1 Background

Daily concern of stock traders is how to execute large quantities of shares with minimal price impact. A term *block order* refers to the initial buy or sell order the trader starts working on. In executing (or filling) a large block order, the trader faces two kinds of challenges: a possible lack of counterparty and the price impact caused. As market resiliency is limited, it is usually unwise to unwind whole trade order block instantly, as it could exhaust the order book by going through bid (ask) price levels, leading to adverse price movement and adverse selection. To avoid this, traders split the large order block, called parent order, into numerous smaller blocks, child orders, and execute each small block separately. After the emergence of high-frequency traders and complex trading algorithms, executing the trade at the main exchange could be disadvantageous due to information leak concerns as other market participants are now able to quickly recognize the trading pattern and move against the trader. As a result, *dark pools* emerged to offer anonymous trading with hidden order books and supposedly no information leakage. Figure 1 below shows the simplified version of value chain in securities trading and highlights which parts the recent changes affect the most.

The nature of equity markets has drastically changed during the past decade. In Europe, with the implementation of MiFID (Markets in Financial Instruments Directive, 2004/39/EC) in November 2007, the rules that bound trading to corresponding home markets were removed. This allowed the emergence of new trading venues, dark pools and multilateral trading facilities (MTFs) that challenged the existing incumbent exchanges, leading to the increased competition in order flow. The fragmented markets, coupled with the increase in electronic order flow and algorithmic trading, changed the way equities are traded in Europe. Clients have traditionally relied on brokers to execute their orders, but now an increasing number of trading venues offer direct electronic access. Trading directly in the market poses new opportunities and threats. In order to hide their intentions and reduce market impact, traders typically slice their parent orders into smaller batches (child orders), and execute them over the day using sophisticated algorithms that seek liquidity in a set of dark pools and lit markets. The liquidity is now spread across multiple trading venues and is partially invisible to traders. The MiFID directive was implemented around the same time than the U.S. equivalent Reg. NMS.

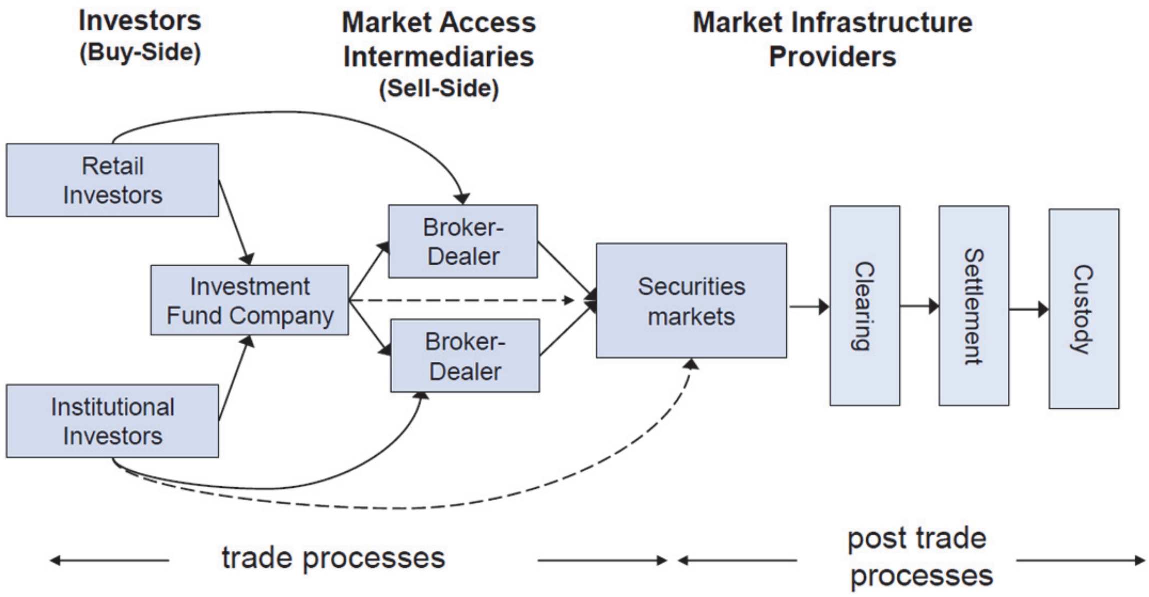

Figure 1: The value chain in securities trading. The focus of this thesis is in Algorithmic Trading, High-Frequency Trading and market infrastructure. In this picture, Algorithmic Trading occurs in *Investment Fund Company* box, High-Frequency Trading in *Broker-Dealer* box, and *Securities markets* is the market infrastructure of stock trading. Source: Gomber, 2012.

More than half of the trading volume across the U.S. and Europe is now done by trading robots, High-Frequency Traders (HFT), that use advanced technology and complex algorithms in order to trade faster than others and gain a competitive edge in trading (see e.g. ESMA, 2016; Gerig, 2015). HFT firms have been criticized for adversely selecting other traders with less advanced technologies and make profit at the expense of other investors. This has been discussed in several academics (see e.g. Brogaard and Hendershott, 2014; Menkveld, 2013; Cartea and Jaimungal, 2014; Biais et al., 2014) and practitioner publications (see e.g. Vuorenmaa, 2013; Agatonovic et al., 2012; Saraiya and Mittal, 2009; Mittal, 2008). HFTs have quickly gained attention of regulators as well (see e.g. Finra, 2014; Shorter and Miller, 2014; Agarwal, 2012; ESMA, 2016) although HFT still lacks a proper definition. As discussed later in this paper, the previous studies on HFT provide quite mixed results. For example, Biais et al. (2014) see HFTs as informed traders compared to other market participants due to their advanced technology and co-location that allow access to relevant information long before others. The information can be anything affecting the share prices from company news to macroeconomic figures. Kirilenko et al. (2013) note how HFTs are able to "buy right as the prices are about to increase". Biais et al. (2014) state this superior ability generates adverse selection for other investors. On the other hand, Hendershott and Riordan (2011) find that on overall, HFTs contribute to price efficiency, thus benefitting rest of the investors.

According to Saraiya and Mittal (2009), the nature of adverse selection has changed and has become systematic with the presence of HFTs. Where adverse selection was previously easy to detect by comparing execution prices to share prices few hours later, they find that adverse selection currently occurs within short time periods of seconds or minutes, cutting into investor's profits fill by fill. Although HFT related adverse selection is difficult to detect and incurred costs per fill are small, the authors find that over the long-term, accumulating small adverse trades over time can cause considerable costs.

Transaction costs play a major role in determining the profitability of investing. While the direct transaction costs have reduced due to the elimination of stock brokers acting as intermediaries, the competition for liquidity is now fiercer than ever and the indirect transaction costs can be substantially higher if trader does not understand the new trading environment and have up-to-date and most sophisticated trading algorithms. Indeed, according to Lovén (2012), the head of EMEA corporate strategy at Liquidnet, buy-side investors have started to see trade execution as more important in terms of the whole investment process. Also, investment firms' client order execution has been put under closer scrutiny as a result of MiFID's best execution obligation. Under MiFID's best execution obligation, investment firms are obligated to "take all reasonable steps to obtain the best possible result when executing orders for their clients". This naturally has increased the pressure to achieve more efficient trade execution. As Aaron Brown (2012), Chief Risk Manager at AQR Capital Management and renowned financial author, stated: "Trade execution is too important to the economy to be left to insiders and regulators. We need broad public education on the subject. Trading execution affects both the efficiency and fairness of capital markets, which means it affects the efficiency and fairness of the economy."

With the advanced methods to discern trading data real time and some HFT firms having a relative speed advantage, traders opt to trade away from displayed (lit) markets and use the opportunity to trade in dark pools instead. Dark pools are currently seen as an attractive alternative to lit markets and are widely used in trading with the promises of reduced market impact and limited adverse selection (Mittal, 2008). According to Bruce et al. (2013), almost every trading algorithm in any major investment firm currently uses dark pools. Some algorithms even trade exclusively in the dark, or use dark pools as a first choice before entering the lit markets. An article published in Kauppalehti[1] in 2013 states that 8% of Finnish stock trades are currently executed in dark pools and the rate is trending up.

As Agatonovic et al. (2012) and Mittal (2008) point out, it is now important to manage information regarding trade orders and intentions. They continue that the more information is leaking through discernable trading patterns, the higher the probability of being adversely selected. Adverse selection phenomenon is typically caused by other traders adversely selecting a trader's resting orders. As dark pools do not publicly display orders sent into them, they supposedly provide shelter from a predatory trader trying to detect resting orders to game for its own profit. In addition, as dark pools typically trade at mid-prices of lit markets and in invisible order books, the information leakage and market impact caused by trader's actions should be lower, improving trade order execution performance.

However, the perception has grown that dark pools may not be as dark as they are supposed to be and they also leak information. As SEC commissioner Aguilar (2015) points out, dark pool operators feel pressure in being able to provide liquidity to customers wishing to trade in the dark. To attract liquidity into these dark pools, some operators have allowed for their own proprietary trading desks or their affiliates to trade within their pools. Some dark pool operators have even given access to high-frequency traders to trade in their pool. As Aguilar (2015) notes, this has led to a conflict of interest between dark pool operators and their subscribers due to operators' need for liquidity providers. There have been cases where dark pool operators have falsely advertised that no proprietary trading is taking place in their pool, while some affiliates have not only engaged in proprietary trading, but have also enjoyed unfair informational advantage against the dark pool subscribers and used it to front-run their trades. The regulators in both the EU area and the U.S. have been trying to place dark pools under stricter scrutiny and heavy

[1] http://www.kauppalehti.fi/uutiset/suomi-osakkeiden-pimea-kauppa-kasvussa/KR4QiWEW 12.9.2013

sanctions have been placed against dark pool operators secretly giving access to proprietary traders. This is discussed in more detail later in this paper.

Transaction costs are directly related to market liquidity and investment firm's ability to use sophisticated methods to find this liquidity. Transaction Cost Analysis (TCA) is used to evaluate the performance in trading execution and traders themselves (see e.g. Garcia, 2005; Ferreira et al. 2012). In the past, TCA has mostly been limited to universe comparisons which can be considered useless at best (Gomes et al. 2010). However, the increased importance of transaction costs to investor performance has led to an increased interest in TCA, leading to more sophisticated trading analytics tools. Using advanced TCA tools, traders can break down exchange's activity around their trades in milliseconds and analyze the exchange's trading tape in post-analysis. In today's trading environment, investing time and effort into proper TCA is crucial in avoiding most toxic dark pools and hiding from predatory traders that would incur adverse selection costs.

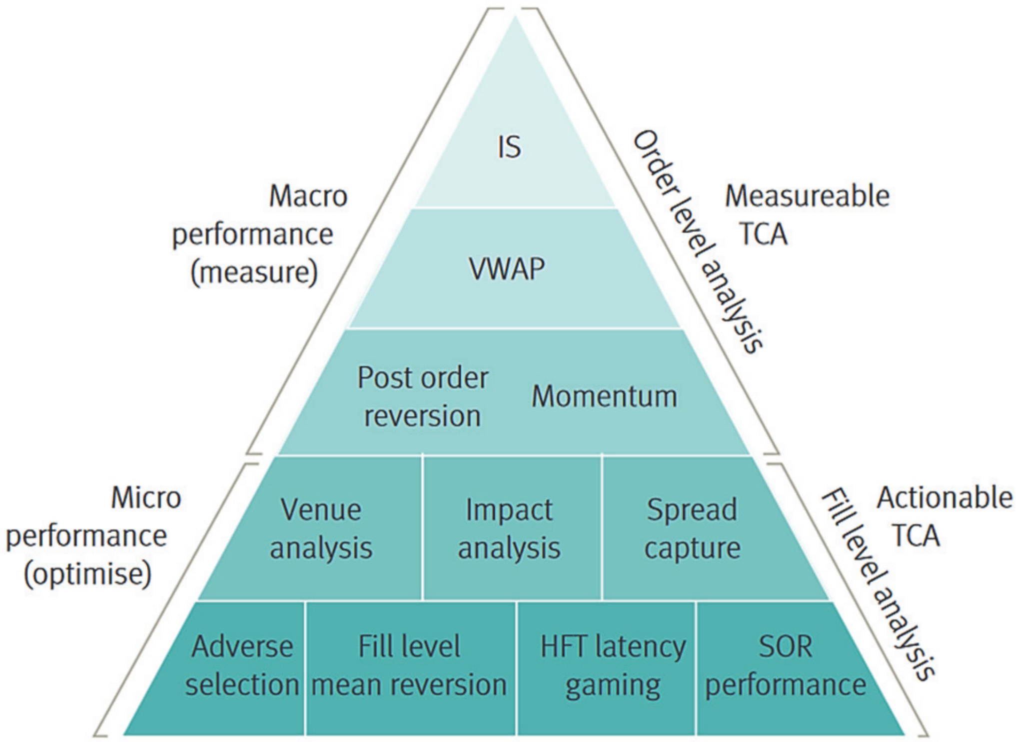

Figure 2: The TCA Pyramid. This thesis focuses on certain areas of the pyramid above: IS, post order reversion and impact analysis. Source: Liquidmetrix

One of the main components in TCA is implementation shortfall (IS), which examines the differences in market prices when the trade decision is made versus the average price ultimately achieved by filling the order. Benchmark for executed trade prices is commonly the price at the moment investment decision was made, or when the trader receives order from portfolio manager. This benchmark, or paper portfolio, is used in measuring the effectiveness of the trade (see e.g. Perold, 1988; Wagner and Edwards, 1993). Kissell (2006) categorizes transaction costs into nine components and presents an expanded implementation shortfall based on the works of Perold (1988) and Wagner et al. (1993). Figure 2 depicts the TCA pyramid as described by Toulson (2013). Implementation shortfall is at the top of the pyramid, meaning it is the most macro level performance measurement. Going down the pyramid goes more into micro level optimization such as adverse selection and Smart Order Router (SOR) performance. The idea of the TCA pyramid is that rather than analyzing just the implementation shortfall, a more comprehensive analysis is in order to answer the question *why* the trade execution is performing or not. This study focuses more on the macro level analysis with the emphasis on IS, post order reversion, impact analysis and adverse selection to a smaller extent.

1.2 Objective and contribution of the study

Using unique trading data of a Finnish asset management firm, this thesis analyzes the trade order execution performance in OMXH25 stocks during and after the order fill. It is done by examining stock price development under different stock liquidity and market volatility conditions. By analyzing the implementation shortfall and price reversion under these market conditions, it is possible to demonstrate under which conditions the performance is systematically better or worse. As this thesis does not focus on micro level analysis on fill-by-fill level, it does not specify whether the individual order fills have been picked off by some other market participants or not. Rather, the intention of this thesis is to analyze, on a macro level, under which conditions the trade order execution performance seems to be systematically worse and if there are signs of information leakage or presence of predatory trading under certain conditions. The results of this thesis could be used in deciding where to look more closely on a micro level.

Transaction Cost Analysis (TCA) is a relatively new concept in trading, becoming important only after the changes in market landscape and the pressure for best execution posed by regulators. Scientific research on TCA is scarce and most of the research is done by agency brokers providing TCA and sell-side trade execution services (see e.g. Toulson, 2013; Sarayia & Mittal, 2009). However, the constituents of TCA such as implementation shortfall and adverse selection are widely discussed topics in scientific research and form the base for this thesis. In addition to describing implementation shortfall and TCA, this paper aims to shed light on concepts such as high-frequency trading and dark pools.

Implementation Shortfall (referred as Slippage or IS) is a widely discussed topic in an academic literature. It is first presented by Perold (1988), who defines implementation shortfall as the difference between paper return and portfolio return, i.e. the price of an asset at the time of the investment decision and the realized price achieved. Perold's (1988) implementation shortfall is a sum of execution cost, opportunity cost and fixed costs. Implementation shortfall was further improved by Wagner and Edwards (1993) who add trading related costs to the formula and Kissel (2006) updated the expanded implementation shortfall to the algorithm-driven trading environment. Finally, Sarayia and Mittal (2009) present a version of the implementation shortfall as an indicator of trading execution performance also used in this thesis.

The new market structure has quickly gained attention among researchers and new papers are continuously being published. High-frequency traders' impact on the stock markets has been especially popular topic among researchers and is still being debated with little consensus. Most of the arguments revolve around the effects on market liquidity and volatility (see e.g. Brogaard, 2010; Chlistalla, 2011; Avramovic, 2012 Jones, 2013; Kirilenko et al., 2013; Menkveld, 2014). Most of the previous research on price development around order fills is focused on child order level data and time intervals are measured in milliseconds to measure adverse selection (see e.g. Polidore, 2012; Toulson, 2013; Saraiya and Mittal, 2009). While adverse selection is a major constituent on implementation shortfall and price reversion, it is not analyzed directly in this thesis (see Sarayia and Mittal, 2009 for more connections between adverse selection and implementation shortfall). Most of the publicly available papers use publicly available data in their analysis. The issue in publicly received data is that it tells only a part of the truth. As traders split their parent orders into numerous trades to be executed in various venues over time, it is close to impossible for researchers using public data to piece together which individual trades are a part of a larger parent order of a specific investor. In addition, a significant portion of the orders are executed in dark pools that provide anonymous trading with hidden order books, further complicating research using only public data. To my knowledge, no publicly available research has been conducted on a proprietary parent order level data from fund management company perspective.

This thesis aims at filling the gaps presented above. Unique proprietary trading data is used to analyze parent order level performance, which is the aggregate performance of smaller child orders executed in various venues over time. The primary purpose of this study is to investigate the market impact caused by orders and the adverse price reversion following an order fill. The market impact and price reversion are studied by using implementation shortfall (IS) as a degree of slippage. If HFTs are indeed negatively affecting the execution efficiency and individual child orders are being picked or gamed, there is a possibility that the current trading algorithms are suspect to leak discernable signals in the stock markets. The observations are sampled by market conditions in order to find evidence whether trade performance in certain conditions prove out to be systemically worse. The research questions and null hypotheses of this thesis are presented on Table 1 below.

Table 1: Research questions and null hypotheses.

Topic	Research Question	Null Hypothesis (H0)
Market conditions and implementation shortfall	Do the market conditions have an effect on implementation shortfall?	H0: There is no evidence of association between stock liquidity and IS
		H0: There is no evidence of association between market volatility and IS
Market conditions and price reversion	Do the market conditions have an effect on price reversion?	H0: There is no evidence of differences in means of price reversion values under different stock liquidity conditions
		H0: There is no evidence of differences in means of price reversion values under different market volatility conditions

In this study, I have the privilege to use very detailed data and sophisticated tools of a big Finnish Asset Management company to analyse their trading execution. However, this approach has its own restrictions too. The findings could be applied only to a limited set of institutional investors or certain markets. Also, as Lee and Radhakrishna (2000) and Finucane (2000) point out, even having access to proprietary order data does not necessarily allow all trades to be identified as buyer or seller initiated. Based on the data available, I argue that the latter problem does not apply to this study as it is easy to identify the trades. Bacidore et al. (2003) argue that measures of quality in trade execution are sensitive to detailed methodological choices, including the method used to average across stocks, the timing and precise definition of the reference quote, which orders and trades are included in the analysis, and order size. I avoid these dangers by using same models as the IFS workstation used as a source and keeping the models and screening relatively simple and clear. However, it is unclear whether the results of this study are comparable to the ones conducted on different institutional investors.

1.3 Methodology and data

The focus of this thesis is stock price development during a parent order execution (implementation shortfall) and after a parent order execution (price reversion). In analyzing implementation shortfall, volume-weighted average price (VWAP) is used to gain the average price achieved. To observe stock prices around various time intervals, European Best Bid and Offer (EBBO) mid-prices are used. Selecting a mid-point price as a proxy for a stock price at any given time is in line with previous studies (see e.g. Saraiya and Mittal, 2009; Polidore, 2012; Toulson, 2013). The EBBO mid-price is defined as the mid-point of the highest bid price and the lowest offer price that is available in the Helsinki Stock Exchange, Chi-X Europe, Turquoise, Burgundy and BATS Europe venues. IFS Liquidmetrix Workstation's TCA tools used in this thesis provides the data on EBBO mid-prices. In implementation shortfall analysis, there are only two time points: a time the trade order is received and a time it is executed. In price reversion analysis, the following time intervals are used to present the price development after the last fill, from 1 minute to 60 minute after the last fill: 1min, 5min, 10min, 15min, 30min and 60min. After the price development over these time intervals have been calculated, an average price change figure for each point in time is obtained by using an arithmetic mean for the observations.

As this thesis aims at finding evidence of systemically better or worse performance under different market conditions, the observations are sampled according to prevailing market conditions. In this thesis, liquidity and volatility are selected to describe the market conditions, as they are popular measurements for market efficiency among researchers. Liquidity is described on a stock level basis by calculating the trade's demand for liquidity from average daily volume for all venues averaged over 3 days. Liquidity is categorized into three categories based on the liquidity being consumed by a trade to *low, moderate, medium-high and high*. *Low* presents low amount of liquidity being consumed, implying best liquidity condition, whereas *high* presents worst liquidity condition as more liquidity is being consumed. To describe market volatility, Euro STOXX 50 volatility index V2X is used. Daily observations are divided into *low, normal* and *high* market volatilities so that each category has an equal amount of observations. Daily index points for V2X volatility index are obtained for the same time period than the trades being analyzed. In addition to analyzing trading performance under the market conditions explained above, the results are broken down to buy and sell orders as it is reasonable to expect buy and sell orders to perform differently under different market conditions.

Overall, the data consists of 4508 observations from the time period of 2.5.2014 – 30.10.2015. All orders are in OMXH25 stocks and the number of stocks traded ranges from 250 to 2,000,000 shares and number of child orders in one parent order range from 1 to 818 with an average of 52. On average, 61.89% of parent order is executed on primary exchange and the rest are executed on MTFs and dark pools. Time period is chosen carefully so there are no major changes to algorithms which could distort the analysis. All observations are obtained by using IFS Liquidmetrix.

1.4 Structure of the study

The structure of this thesis progresses as follows. Chapter two discusses the key concepts such as high-frequency trading, algorithmic trading, fragmented markets, dark pools, transaction costs and transaction cost analysis (TCA), providing literature background for the thesis. Chapter three presents the hypotheses of the study and chapter four presents the methodology and data used for the analysis. Chapter five presents the results and chapter six finally discusses the findings and concludes this thesis.

2. Research background

Financial markets have evolved at a significant pace the past years. Where before trading was done in trading pits through brokers, now traders are concerned with bizarre concepts such as high-frequency trading, latency trading, predatory algorithms, slippage, dark liquidity and dark pools. In equity trading, which is the focus of this study, every millisecond counts and huge investments are made into the hardware and sophisticated algorithms to improve the trade execution quality. This chapter describes the major changes in equity trading and sheds light into the concepts still vague to many investors and researchers. At first, high-frequency trading is explained as it is currently one of the most controversial topics in trading. The reasons behind the emergence of high-frequency trading and arguments both for and against high-frequency trading are presented with regulators' views on the topic. Second part of this chapter focuses on the changing landscape in financial markets infrastructure, explaining the fragmentation of financial markets and the emergence of multi-lateral trading facilities and dark pools while also briefly discussing the enabling regulatory changes leading to this new trading environment. Lastly, this chapter discusses the transaction cost analysis of trading, with the focus on price impact and implementation shortfall.

Majority of prior literature is focused on NYSE and NASDAQ exchanges in the U.S. Analyzing proprietary NYSE system order data, Peterson and Sirri (2003) and Werner (2003) come to similar conclusion that prices move significantly in the directions of the trades before execution. This adverse movement in quotes before execution could be caused by information leaks of pending orders ahead of trades. It could also reflect large orders sliced into smaller ones sent to market in succession, or it may reflect similar reaction of several traders to common information events where quotes are being revised after the earliest orders are executed.

2.1. High-Frequency Trading

Until recently, not much was known about High-Frequency Trading (HFT). After linking HFTs to numerous short-term market shocks, *flash crashes*, investors slowly became aware of this new market player. So far, the biggest shock related to HFTs is the infamous

Flash Crash of May 6th 2010. Finally, the bestseller book *Flashboys* written by Michael Lewis drew the attention of general public towards HFTs. Many buy-side investors view HFT as detrimental to their business and try to avoid trading with them. However, in the current financial market environment, it is close to impossible to trade without transacting with HFTs and the concern of their detrimental effects could be, while warranted, a little overblown as discussed later in this chapter. This chapter discusses HFT more closely and presents previous literature research regarding HFT and algorithmic trading (AT).

2.1.1 Characteristics of high-frequency trading

High-Frequency Trading (HFT) refers to use of high speed and proprietary trading algorithms. Although as of now HFT does not have a clear definition, it is lauded by SEC (2010) as "*the most significant market structure development in recent years"*. For the lack of clear definition, SEC's (2010) concept release identified five characteristics often attributable to HFTs:

1. Use of extraordinary high speed and sophisticated programs for generating, routing, and executing orders.
2. Use of co-location services and individual data feeds offered by exchanges and others to minimize network and other latencies.
3. Very short time-frames for establishing and liquidating positions.
4. Submission of numerous orders that are cancelled shortly after submission.
5. Ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions overnight).

However, a proprietary trading firm does not have to meet all of the mentioned characteristics to be classified as HFT by SEC. In Europe, the upcoming MiFID II attempts to define HFT as following: *"High frequency algorithmic trading ("HFAT"): An algorithmic trading technique characterized by… infrastructure intended to minimize network and other types of latencies… system-determination of order initiation, generation, routing or execution without human intervention… or high message intraday rates" (ACA Compliance Europe, 2016).*

Despite the lack of proper definition, HFT has lately been a topic of heated debate and has raised concerns among the investors. In the view of the proponents of HFT, it is only a matter of normal evolution in financial transacting and serves to increase liquidity and market depth. On the other hand, opponents claim the HFT does not increase market liquidity, but rather deteriorates it. They further accuse HFT for making the financial markets more opaque and unequal as the market participants with the highest speed and best locations gain unfair advantage and arbitrage opportunities. While the reality might be somewhere in between of these views, HFTs have gained negative publicity with so-called *flash crashes*. The most infamous of them is the Flash Crash of May 6th, 2010 when U.S. stock market indices, stock-index futures, options, and exchange-traded funds suddenly plunged by more than 5 percent in less than five minutes, some securities as much as 60%, before rebounding almost as quickly (SEC, 2010).[2]

After the emergence of HFTs in the early 21st century, they have quickly become a driving force in trading. In U.S., the HFT accounts for approximately 55% of trading volume in equity markets (Gerig, 2015). HFT has been growing fast in Europe as well. According to European Securities and Markets Authority's (2016) analysis of EU's equity markets, HFTs account for 49% of the number of trades, 76% of the number of orders, and 43% of the value traded. They note that there are significant differences in HFT activity between trading venues, with BATS Europe, Chi-X Europe and Turquoise having the highest levels of HFT activity. Vuorenmaa (2013) approximates that the HFT accounts for around 20% of the total trading volume in NASDAQ OMX Helsinki.

Biais et al. (2011) note that although HFT strategies are diverse, they share one common feature: the reliance on the ability to run real-time data analysis, decision making processes, and trade order execution accordingly at a very high speed. To be able to do this, HFT firms invest heavily in hardware, algorithms, highly qualified personnel (e.g., Ph.Ds in computer science, mathematics and physics etc.), expensive real-time data feeds, and ultra-fast connections to trading venues' matching systems. HFTs analyze massive amounts of market data and use the advantage of high speed to exploit trading opportunities that may open up for mere milliseconds. The advantages are typically marginal, but by accumulating small advantages over time, HFTs are able to generate large

[2] Kirilenko and Lo (2013) claim that, contrary to popular belief, HFTs did not cause the flash crash after all but served to significantly amplify the effect.

profits (Chlistalla, 2011). O'Hara (2015) breaks HFTs into two main gradations: Low latency and ultra-low latency. Low-latency trading refers to very fast connections and trading speeds, while ultra-low latency trading is dependent on being at the physical limits of sending orders to matching engines of trading venues. Order latencies are usually measured in milliseconds, microseconds or, in some cases, even in nanoseconds. To put things in perspective, it takes 300 to 400 milliseconds for human to blink an eye. (O'Hara, 2014)

As Chlistalla (2011) notes, exchanges and other trading venues have found new monetization opportunities by selling co-location services for speed-sensitive market participants. By selling co-location services, the trading venues sell the rights to install traders' own hardware in a physical proximity to venue's matching engine, resulting in faster connection relative to other traders without co-location. The competition for continuous order book and arbitrage opportunities is fierce among HFT firms, and massive investments are made to win even a few milliseconds. Some studies have concluded that this competition has led to a so-called "socially wasteful arms race" among HFTs which puts ordinary investors at a disadvantage. The concern is that the resulting adverse selection could reduce market quality measured by liquidity and price informativeness. (see e.g. Biais et al., 2011; Menkveld, 2014; Budish et al., 2015; Schwartz and Wu, 2013). Most HFTs want to be at the front of the queue when an attractive order arrives. This requires a good understanding of the structure of the market and the matching engine itself. According to SEC's (2014) research, as much as 95.6% of all HFT orders are canceled. The high cancellation rates among HFTs are caused by continuous adjustments in positions in order books. If the placed order turns out to be unfavorable, HFT quickly cancels it before any participant can match the placed order.[3] (SEC, 2013; SEC, 2014)

Hendershott et al., (2011) reminds that the term algorithmic trading (also referred as algo trading or AT) is often mistakenly mixed up with HFT. While HFT is a subcategory of algorithmic trading, AT refers to broader use of computer algorithms in trading. Trading algorithms were originally developed for trading optimization, enabling execution of large orders gradually over time, thus reducing market impact and trading costs. Basically, a trading algorithm breaks one large parent order into numerous smaller child orders it then

[3] See Data Highlights 2013-05: The Speed of Equity Markets (October 9, 2013) and Data Highlight 24-02: Equity Market Speed Relative to Order Placement (March 19, 2014)

tries to execute with the best possible prices across different trading venues, while closely tracking performance benchmarks over the execution interval. Algorithms typically determine the timing, price, quantity, and routing of orders while continuously monitoring market conditions across different securities and trading venues. (Hendershott et al., 2011)

2.1.2 High-frequency trading strategies

High-frequency trading technology allows for a wide variety of different trading strategies. Many of the strategies are not new per se, but rather old ones updated to work in current market structure. Investors seek to minimize their trading costs by using advanced technology and sophisticated trading algorithms, while opportunistic proprietary traders try to discern the patterns used by institutional investors in order to trade for their own profit. High-frequency trading strategies can roughly be divided into two main categories: Passive market makers and opportunistic trading strategies. This chapter analyzes different HFT strategies in more detail.

SEC (2014) presents four broad categories for HFT strategies: i) Passive market making, ii) Arbitrage, iii) Structural, and iv) Directional. In short, passive market making strategy is not dependent on directional price movements, but rather a passive strategy to gain profit in the form of spreads and rebates. Arbitrage strategy aims to find arbitrage opportunities between related products and markets, relying on the price convergences. Structural strategy seeks to take advantage of structural vulnerabilities in the market structure or in certain market participants. Lastly, directional strategies can be either order anticipation strategies, where an HFT seeks to find large buy and sell orders to trade ahead of, or momentum ignition strategy, where HFT enters a series of orders in an attempt to ignite a rapid price movement followed by price momentum.

Angel and McCabe (2013) provide comprehensive breakdown of the most common HFT strategies in an attempt to answer the question about the fairness of high-frequency trading. They discuss in detail the following ten HFT strategies:

1. Market making

2. Arbitrage

3. Pairs trading and statistical arbitrage

4. News Reaction Strategies

5. Technical and other predictive strategies

6. Order discovery strategies

7. Front-running

8. Order triggering strategies

9. Spoofing

10. Wash sales

Market making is a strategy where HFT places passive orders to provide liquidity and make profit from the bid-ask spreads. The buy and sell orders do not arrive in markets at exactly the same time. Investors need to sit on their orders waiting for an acceptable bid and offer prices, exposing themselves to liquidity risks and unfavorable price movements. Market makers are seen as stabilizers of stock markets as they act as providers of liquidity by placing both bids and offers at the same time, while making profit from the bid-offer spreads. Previously this was done by broker-dealer firms placing the orders on the trading floor, and now it is all done by computer algorithms. Using high-frequency technology, these market makers continuously maintain and update market-making quotes. As the large rate of cancelled orders in order book has been one of the main points by critics of HFTs, one needs to understand that updating the quotes requires market makers to cancel and place new orders at a very high frequency to provide up-to-date bid and offer rates. Market making strategy is seen as a positive one as the market making HFTs provide liquidity and increase the smoothness in equity markets. As a result, investors could trade larger quantities without causing excessive price movements. (Angel & McCabe, 2013)

Arbitrage is another highly used HFT strategy and it takes advantage of temporary mispricing between related financial instruments. For example, HFT could trade Exchange Traded Funds (ETFs) and underlying stocks simultaneously, profiting from the temporary mispricing between these two. This strategy helps to draw the prices of related financial instruments closer, reducing the difference known as basis. As this strategy contributes in keeping the prices of ETFs and their constituent stocks in line, it is seen as increasing the fairness of equity markets to retail investors who invest through ETFs. Because these arbitrage opportunities are simple, they disappear very quickly. For this reason, there is a competitive race between HFT arbitrageurs to take advantage of these profitable trading strategies before they disappear. (Angel & McCabe, 2013)

Pairs trading and statistical arbitrage strategy takes advantage of the fact that there are many economically related financial instruments whose prices tend to move in tandem even with no strict arbitrage relationship between them. In this strategy, traders bet on the eventual convergence of share prices between economically related companies and try to trade accordingly when short-term price divergence occurs. In algorithmic trading era, traders can now look beyond simple stock pairs and seek for large groups of related instruments that tend to move together. (Angel & McCabe, 2013)

HFTs implementing *news reaction strategies* trade on major announcements that have an effect on stock prices. The competition among HFTs in this strategy has also been stiff and HFTs continuously seek new ways to process the information faster. (Angel & McCabe, 2013) Now, HFT algorithms scan not only the most well-known commercial news providers, but also Twitter feeds in order to be able to trade on the news before anyone else (see e.g. Philips, Bloomberg, 2013). There has been some controversy to this strategy, especially when Thomson Reuters got caught in 2013 by releasing an influential consumer survey for a fee to some HFTs two seconds earlier than anyone else, allowing HFTs to trade on new information before others (Javers, 2013).

Technical and other predictive strategies have been used since the dawn of stock trading. The idea is to analyze the recent price data in an attempt to predict future price movements. This old strategy is now actively used by HFT firms that use high-speed computers and algorithms to seek out forming trends or upcoming price reversals to take advantage of. (Angel & McCabe, 2013) An example of this is market microstructure trading, or “trading the tape” strategy, which involves analyzing the quote flow in order to extract price information and reverse-engineer trading party order flow to try to predict likely future volumes of buy and sell orders and thereby anticipate price momentum trends. On example of this trading strategy is so-called filter trading which involves monitoring large amounts of stocks for abnormal price changes or volume activity (see e.g. Rowley, 2010).

Order discovery strategies attempt to discover the existence of larger orders that have not been filled. HFTs typically "ping" the market with a small order to see if there is any trading interest for the instrument. If the small order gets filled quickly, it could indicate the existence of large block trade being processed, allowing the HFT to take advantage of it by trading accordingly. This is a major concern for big institutional investors who try to hide their orders to minimize the market impact and adverse selection of their trades. Most of the HFTs now try to discern certain trading patterns in order to identify the investor behind the trades because being able to trade against a huge institutional investor, such as pension funds and hedge funds, poses a profitable opportunity for more agile proprietary HFT firms. (Angel & McCabe, 2013) There has been controversies around this activity as well. In 2011 Pipeline Trading Systems had to cease its operations after being caught from front running its clients. The company provided institutional investors a dark pool where they could trade anonymously, but did not disclose it had its own active proprietary trading desk trading against the investors using the order data for its own advantage (SEC, 2011).

Front-running is an illegal trading strategy where a market participant discovers that another investor is about to make a large transaction and then "runs in front" of the trade. For example, consider a case where a broker receives a large buy order that takes hours or days to fully execute. With the knowledge that this buy order will push the price up, the broker could buy the shares for its own account before executing the client's order. This leads to adverse price selection for the client and an illegal arbitrage opportunity for the broker. The critics of HFTs argue the use of high-frequency technology can be used to front run other orders. Some trading algorithms seek to find out if a large order is in process and then jump in front of it in the order queue. This is also called predatory high-frequency trading. This strategy is close to predictive and order discovery strategies discussed above and it is difficult to accurately discern these strategies due to their similarities. The fragmented markets and anonymous trading in dark pools makes it even more difficult for the authorities and other market participants to identify when front-running occurs. The HFTs tend to operate on a grey area as order discovery strategy is legal itself but front running is highly illegal. (Angel & McCabe, 2013)

Bear raid strategy is a classic example of an order triggering strategy. Using this strategy, the raider enters a short sale order large enough to push the price down, leading to larger sell-off as other investors may think that someone has more information than others. If the price falls enough, it may again trigger further sales caused by stop-loss orders and liquidated margin accounts, further depressing the shares prices. After the price has fallen enough, the raider buys the shares back at a lower price to cover for the short and makes a profit out of it. Sophisticated high-frequency algorithms can be used to seek out potential targets, such as shares with unbalanced trade book, for this kind of abusive strategy. (Angel & McCabe, 2013)

Spoofing is a trick used to take advantage of automated market makers. Consider an example where an investor wants to buy 10 000 shares with current bid and offer prices of €10.00 and €10.02 respectively. The high-frequency algorithm then identifies these prices are probably offered by market maker algorithms that automatically adjust to prevailing market conditions. Using the high-frequency algorithms to its advantage, the HFT places a sell order of €10.01 triggering a quote matching algorithm to come down to offer price of €10.01 as well. After this, the HFT cancels its sell order and immediately places a buy order of €10.01, thus saving €0.01 per share on the purchase. (Angel & McCabe, 2013)

Wash Sales is another manipulative trading strategy used by HFTs where the intent is to make it appear that there is more trading activity on the stock than there really is. The manipulator may place simultaneous buy and sell orders through different accounts to trick other investors into thinking that there is trading interest in the stock. The manipulator continues this at higher and higher prices, slowly dragging the price upward and making it appear there is more liquidity and upward price pressure on the stock. The intent is to attract more trading interest in the stock while ultimately unloading the sell order at a higher, manufactured, price. (Angel & McCabe, 2013)

While being excluded from the list above, *Quote stuffing* is an HFT strategy worth mentioning. Lattemann et al. (2012) describe it as very problematic trading strategy that not only increases the cost of trading, but also serves to skew the apparent market liquidity and bid-ask spreads. Quote stuffing is another abusive trading strategy where trader uses high-speed computers to send thousands of orders into the market only to cancel them immediately after. The purpose is not to trade, but rather to slow down other traders with slower computers by the massive message traffic and then benefit from the temporary price distortions. Intentional quote stuffing is an abusive and strictly illegal activity, but the high cancellation rate does not necessarily mean the existence of quote stuffing. As discussed above, market makers tend to have high cancellation rates as well. However, the excess cancellations are a form of pollution that imposes costs on everyone who have to deal with the massive quantities of data generated, such as traders and trading venues. Lattemann et al. (2012) argue that because of quote stuffing activity, the apparent market liquidity and bid-ask spreads are no longer reliable indicators on market liquidity and efficiency. They compare quote stuffing to e-mail spamming and claim it is one of major reasons that investors are moving their trading activity towards dark pools.

Numerous studies conclude that most HFTs act as market makers and help to improve the liquidity and reduce the volatility in stock markets. However, Carrion (2013) and Brogaard et al. (2013) find evidence that more than 50% of HFT activity is attributable to aggressive, liquidity taking orders after analyzing NASDAQ Datasets. The level and nature of HFT activity also varies greatly across different types of stocks. For example, Brogaard et al. (2013) conclude that HFTs are much less active in small-capitalization stocks than in large-capitalization stocks. They also note that 69% of this small-capitalization stock activity is attributable to aggressive orders instead of passive orders typically related to market making.

Baron et al. (2012) argue that the markets are effectively a “zero sum game” where HFTs generate their profits at the expense of other traders, and these profits are highly concentrated toward a small number of the fastest and most aggressive firms. Only the fastest and most clever HFTs survive and they have a significant advantage over other market participants.

The trading is now so fast that it is not enough to have the fastest connections and algorithms. You have to be geographically close to the exchange or ECN in order to beat other traders in speed. As Laughlin et al. (2014) and Angel (2014) point out, the limiting factor is the speed of light. Therefore, in order to realize greater benefits from low-latency strategies, HFT and other algorithmic trading firms engage in the practice of “co-location”, where they move their servers into same facilities with the exchange’s servers. This has opened a new way for exchanges, dark pools and ECNs to increase their revenues by selling space in their facilities next to their servers. For example, CME Group created a 428,000 square-foot data center in Chicago for the purpose of selling co-location services (see Bowley, 2011).

2.1.3 High-frequency trading and its effect on financial markets

The previous literature provides inconclusive results on HFT's impact on market quality and efficiency. One of the most frequently used claim in favor of HFT activity is that it can improve the market liquidity by reducing the bid–ask spreads within a market and by strengthening the linkage and activity across related markets. Topics of concern and debate typically range from HFT's effects on liquidity, price formation and volatility. This chapter discusses the findings in related researches, bringing up points from both against and for high-frequency trading.

Hagströmer et al. (2014) finds mitigating effect of HFTs on volatility as HFTs submit less aggressive orders when the market volatility is high. Moreover, Lepone (2011) and Hagströmer and Nordén (2013), provide global evidence that HFTs stay active during both high– and low–volatility periods, and that HFTs have usually remained as primary providers of liquidity in periods of high uncertainty, and that HFTs have mitigated intraday pricing volatility. Avramovic (2012) finds that long-term volatility has remained within historical norms, while the short-term volatility has steadily declined. He concludes that markets are at least not worse off in the presence of HFTs.

Brogaard (2010) examined the HFTs' impact on the U.S. equity market by analyzing market characteristics such as liquidity, price discovery and volatility. He finds that HFTs add substantially to the price discovery process, provide the best bid and offer quotes and may help to reduce volatility. After surveying approximately 30 theoretical and empirical papers of HFT, Jones (2013) attempts to conclude that HFT and its related technologies improve the financial markets by reducing trading costs and improving market liquidity. Brogaard et al. (2014) analyzed the role of intermediary HFTs in price discovery and price efficiency on the NASDAQ exchange. They find no evidence of HFTs negative impact on price stability. To the contrary, they conclude that HFTs trade in the direction of reducing transitory pricing errors both on normal and on the most volatile trading periods. After examining HFT activity on the London Stock Exchange, Jarnecic and Snape (2014) find similar results that HFTs help to resolve temporal liquidity imbalances in the limit order book. Hasbrouck and Saar (2012) conclude that the increased low latency trading improves market quality by lowering short-term volatility, decreasing spreads, and increasing displayed depth in the limit order book. However, they acknowledge the dangers of severe market conditions when HFTs contribute to market failures such as flash crashes. Angel and McCabe (2013) find similar results and show that HFT contributes in increasing the market efficiency and liquidity, resulting in lower transaction costs for investors. However, they also point out the detrimental effects of predatory trading strategies that seek to abuse investors' trade orders which only serve to move prices away from their fundamental values.

While Chlistalla (2011) agrees there is no proof about HFTs' negative impact on market liquidity, he reminds issues still remain. Unlike traditional market makers, HFTs are not obliged to provide liquidity during more stressful periods such as during periods of high volatility. This could lead to a lack of liquidity during stressful periods. In addition, HFTs' contribution to market depth is marginal due to the small size of their quotes. As a result, larger orders may have to transact with many small orders, going through the order book, resulting in higher realized transaction costs than anticipated. He also notes that the provided liquidity by HFTs might be misleading because the average duration of HFT orders is very short as they are usually cancelled within milliseconds after placing them. Anand and Venkataraman (2013) find supporting evidence that market-making HFTs on the Toronto Stock Exchange withdraw from the market in unfavorable conditions. Hendershott and Riordan (2011) find that price discovery benefits from algorithmic trader quotes that quickly detect anomalies in prices and correct them. On the other hand, HFTs may indirectly distort the price formation if they create an incentive for traders to place natural liquidity into dark pools as a way of avoiding transacting with ever-decreasing order sizes. Jarrow and Protter (2011) created a theoretical model to monitor HFT activity. They find that HFTs, triggered by a common signal, place a same order at the same time, collectively acting like one big trader creating price momentum and causing prices to be less informationally efficient. Kirilenko et al. (2013) finds that the HFTs have a quantifiable effect on volatility and conclude that there should be an HFT premium in volatility for stocks actively traded by HFTs. They further claim that the automated execution of large orders can create a feedback-loop or vicious cycle effects under certain market conditions. These could escalate to destabilizing market events, flash crashes, like the one we saw in May 6th, 2010.

McInish and Upson (2013) analyzed the execution quality around the time when NYSE decreased its latency in March 2008. The results suggest that the execution quality of HFTs had a drastic increase, while the execution quality of slower traders had only a slight increase. Ye et al. (2013) also analyze the impact of two NASDAQ technology upgrades implemented in 2010 and find evidence of increased rate of cancelled orders, while overall trading volume, bid–ask spread and order book depth remained the same. They suggest this is an evidence of diminished liquidity in faster exchanges. On the contrary, Brogaard et al. (2014) analyzed latency decreases on the London Stock Exchange and find evidence of increased HFT activity but do not find clear evidence of changes in the transaction costs of institutional investors.

In addition, Egginton et al. (2016) note that an HFT practice called quote stuffing results in higher costs and worsens the market quality. Biais et al. (2011) note that while making profit from fast trading, HFTs can increase adverse selection, price impact, and generate negative externalities, where there may be more investment in HFT than is societally optimal. Bershova and Rakhlin (2013) and Gao and Mizrach (2016) present evidence of association between HFT activity and increased volatility, though they do not separate the effects of aggressive and passive HFT. Breckenfelder (2013) finds that the competition among HFTs increases the intraday volatility but has no effect on interday volatility. He finds that the ratio of liquidity consuming trades to total trades of HFTs doubles from 30% to 60% when HFTs compete for volume.

Menkveld (2014) concludes that while HFTs might improve markets when they act as market-makers, they impair the markets when HFTs pick off investors' quotes at superhuman speed on information that would have been revealed to investors anyway a little later. He brings up the same problem of socially wasteful arms race than Biais et al. (2011) do in their research. By socially wasteful arms race, they mean the overinvestment in technology in order to be ahead of rival HFTs. Cartea and Penalva (2012) present a GM model where HFT is able to intermediate trades between liquidity traders and market makers due to its rapid execution and information processing ability and use the model to examine the effects on financial markets. They claim that HFTs increase the market impact of liquidity trades, increase price volatility and double trading volume concluding the presence of HFTs have distorting effects on the market conditions.

When assessing the effect of HFT on market quality, it is imperative to recognize the diversity of HFT strategies. The focus on only certain types of HFTs can be one of the reasons why previous studies of HFTs come up with so contradictory results. Generally, the studies indicate that the passive, market making HFT strategies appear to have beneficial effects on market quality by reducing spreads and intraday volatility on average. After analyzing Dutch stocks, Jovanovic and Menkveld (2011) find that the entry of a large, primarily passive HFT firm was associated with a 15% decline in effective spreads. Hagstromer and Norden (2013) find similar results in Swedish equity markets where the increase in passive market-making activity was associated with a decrease in short-term volatility. Constraining the HFTs by regulations could be problematic and cause unexpected results, as is shown in the study by Malinova et al. (2013). They find that an increase in regulatory fees mostly affecting high-frequency market making firms led to a significant increase in quoted and effective spreads in the Canadian equity markets, concluding that regulatory effects on HFT may only serve to decrease the market functionality if the regulation is ill-placed and focuses on market makers.

In contrast, primarily aggressive HFT strategies come up with more mixed results and raise potential issues. On the one hand, aggressive HFT strategies can improve certain dimensions of price discovery as presented by Brogaard et al. (2013). They claim that aggressive HFT activity improves price discovery efficiency in the NASDAQ market by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. On the other hand, some other papers come up with more mixed results. For example, Zhang and Riordan (2011) note that the information impact of HFT depends on the stocks. They find evidence of significant information impact in large-cap stocks, inconclusive evidence in mid-cap stocks and significantly lower information impact in small-cap stocks. Benos and Sagade (2012) find that in the U.K. equity markets aggressive HFT activity generates both significantly greater permanent price impact and significantly greater noise than non-HFTs. In addition, Zhang (2012) finds that aggressive HFT dominate price discovery in the short run, but that passive non-HFTs have a higher contribution to price discovery in the longer time period.

As discussed in this study, the implementation shortfall (IS) costs are the most used benchmark to analyze the transaction costs. Tong (2014) finds that an increase in HFT activity on the NASDAQ market is associated with higher implementation shortfall costs incurred by institutional investors. On the other hand, Bershova and Rakhlin (2013) argue that HFT activity in the Tokyo and London equity markets is negatively correlated with the transaction costs of long-term investors. However, neither of these studies separate these effects into aggressive and passive HFT activity.

Goldstein et al. (2014) point out that in most rapid trading strategies the orders last only for a few milli- or microseconds. There is also evidence of some HFT strategies with no intentions of carrying through the trade orders, but instead to cancel it almost immediately after placing it. These so-called false orders are used as a "pinging" tactic to find the price other traders are willing to pay or to discover undisplayed liquidity. This is most often done in the form of Immediate-or-Cancel (IOC) orders (see e.g. SEC, 2010, p. 3607). While this may be part of a normal price search mechanism, these practices, also called as "flickering quotes" or "quote stuffing", can cause an overload of data in market centers. This practice can hamper market quality. Egginton et al. (2016) find that during periods of intense quoting activity, stocks experience decreased liquidity, higher trading costs and an increase in the short-term volatility. Some HFTs deliberately use quote stuffing practices in order to slow other market participants in order to cause profitable price distortions.

2.1.4 Regulation to high-frequency trading

As Menkveld (2014) notes, the HFTs quickly caught the attention of the general public because of a few extreme and dramatic momentary price drops or spikes the past few years of which the Flash Crash in May 2010 is the most notorious one (see U.S. Securities and Exchange Commission and the Commodity Futures Trading Commission [SEC/CFTC], 2010). Such events have naturally raised questions and doubts about the risks of HFT and whether it needs more constraints or oversight. The regulatory authorities have been more and more aware of this and for example the Financial Industry Regulatory Authority (FINRA 2014) has identified HFT as an enforcement priority for 2014. FINRA noted that "although many HFT strategies are legitimate, some are not and may be used for manipulative purposes" and that the surveillance of abusive algorithms remains a high priority for FINRA.

The history of HFTs dates back to 1998, when SEC passed the Regulation Alternative Trading Systems (Reg. ATS) in order to restrict the exchange monopoly enjoyed by NYSE and NASDAQ. This resulted in an emergence of a number of alternative trading platforms. In 2001, U.S. stock exchanges started quoting prices in decimals instead of fractions, narrowing the minimum spreads from $1/6^{th}$ of a dollar to one cent. In 2005, in order to promote transparency and competition between markets and to require trade orders to be posted nationally and not at individual exchanges, the SEC passed the Regulation National Market System (Reg. NMS). As a result, traders were able to leverage and profit from any small price differences between exchanges–if they were fast enough. (Agarwal, 2012)

The HFT enabling regulations were implemented around the world in early 21^{st} century. In Europe, Markets in Financials Instruments Directive (MiFID) was introduced in November 2007. Similar to Reg.NMS, the aim was to abolish concentration and to increase competition between financial markets, bringing down the trading costs across Europe. Regulations aimed at improving competition and market transparency together with modern, sophisticated technologies have acted as catalysts in the development of high-frequency trading. Over the past few years, regulators have now started to question HFTs' impact on the financial markets and have put proposals to restrict HFT business. The tools considered range from implementing new trading taxes to directly banning certain strategies. (Agarwal, 2012)

In January 2010, the SEC commented on the impact of HFT strategies on the quality and integrity of markets in its concept release. After the flash crash, a joint committee was formed between SEC and CFTC to provide advice on emerging regulatory concerns in May 2010. In February 2011, the committee published a report with regulatory response recommendations to the flash crash. In Europe, after the European Securities and Markets Authority (ESMA) called for evidence on issues in the European equity markets, the European Commission's MiFID Review Consultation document put forth regulatory proposals on HFT in December 2010. (Agarwal, 2012) The following years the SEC has implemented several regulations and systems aimed at restricting the adverse behavior of HFTs. These include MIDAS, the Consolidated Audit Trail, Regulation SCI, Large Trader Reporting Rule, rule 15c3-5 to prohibit HFT firms from receiving naked access and introduction of new circuit breakers (Shorter & Miller, 2014).

In Europe, the EU is implementing an updated MiFID known as MiFID II in an effort to establish more safe and transparent financial system. MiFID II includes the first EU-based regulatory curbs on HFT activities, including the requirement to install circuit breakers, requirement to get authorization by regulators on trading algorithms and the obligation to store all trade order and cancellation history that is made available to the authority upon request. (Shorter & Miller, 2014)

2.2 Stock market infrastructure

The financial market infrastructure has seen drastic changes the past years. Trading pits are all but extinct and most of the liquidity is found in alternative trading venues instead of main exchanges. New trading venues started to emerge when changes in regulation (Reg. NMS in U.S. and MiFID in Europe) opened up the competition. This chapter discusses the most important changes in market structure and the characteristics of financial markets today.

2.2.1 Evolution in market structure

While high-frequency trading and algorithmic trading emerged quite recently, computerized trading itself is not new. As can be seen from timeline of Figure 3, computerization of trading started in the early 1970's when NASDAQ became the first electronic stock market. In 1976, the New York Stock Exchange (NYSE) implemented a *designated order turnaround* (DOT) system and Super-DOT system later in 1984, allowing traders to post trade orders electronically (Markham & Harty, 2007). NYSE and NASDAQ exchanges had a duopolistic status until late 1990's when SEC authorized electronic communication networks (ECN) with its Regulation Alternative Trading Systems (Reg. ATS) in 1998, allowing trades to be executed outside of the traditional exchanges. As alternative trading systems emerged, new computer systems were developed in order to enter and execute trade orders electronically by algorithms. The market structure changed again in 2001 with the decimalization of the exchanges, changing the minimum stock tick size from 1/16th of a dollar to 0.01$. The decimalization narrowed the bid-ask spreads and altered the advantage of market-makers, further encouraging algorithmic trading. Finally, SEC implemented the Regulation National Market System (Reg. NMS) in 2005 to modernize and improve the stock markets, opening up the competition for order flow. (McGowan, 2010)

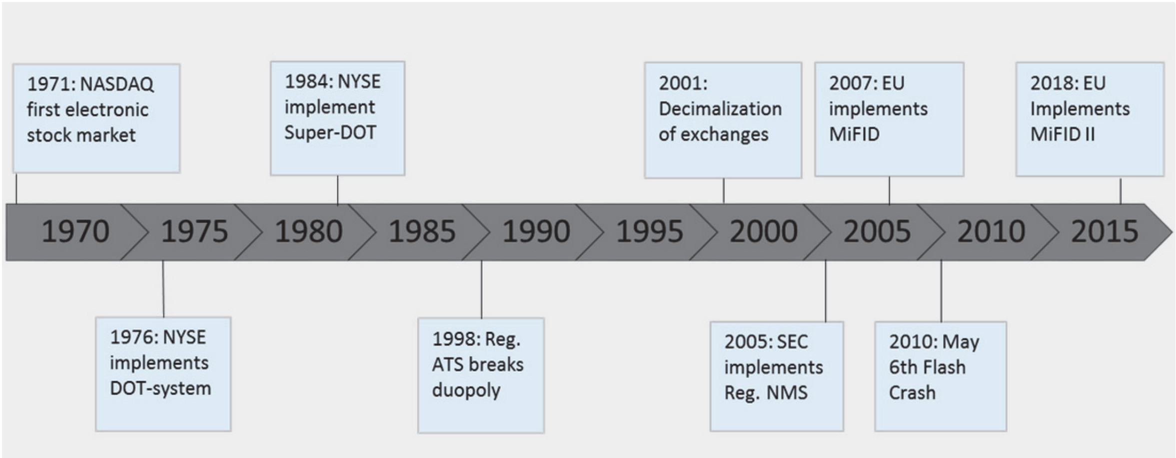

Figure 3: Timeline of important events that changed market infrastructure and trading.

Europe saw a similar change in stock market structure with the implementation of MiFID directive in 2007. Davies (2008) argues the directive *"is the most significant European Union legislation for investment services in each of the EU member states."* MiFID allowed European financial institutions to operate more freely in other EU host states and removed the concentration rule, opening up the competition for order flow similar to Reg. NMS in the U.S. The regulatory changes in both the U.S. and Europe resulted in an emergence of new trading venues, disturbing the power balances in financial markets. In Europe, the alternative trading platforms are called Multilateral Trading Facilities (MTFs). With the emergence of new trading venues, new trading algorithms and Smart Order Routers (SOR) were introduced to find the liquidity that is now spread among the venues. While these regulatory changes have improved the financial markets dramatically, they have also led to some unpredictable and controversial problems. (see e.g. Davies, 2008; McGowan, 2010)

2.2.2 Multi-Lateral Trading Facilities and Dark Pools

The Multi-lateral trading facilities' (MTF) share of total trading volume has rapidly increased after the implementation of MiFID directive. Contrary to U.S. equity markets, there is no official consolidated tape to establish European Best Bid and Offer (EBBO), meaning that the different trading venues are not formally linked and price formation is not enforced across the trading venues. The similarity in prices across trading venues is left at the hands of competition instead. Early post-MiFID multi-market trading researches

(Hendershott et al., 2011; Jovanovic & Menkveld, 2011) point out problems associated with the lack of formal linkages. However, the rise in algorithmic trading and high-frequency trading has resulted in a convergence of price formations and increase in liquidity as traders may intermediate in different trading venues using sophisticated trading algorithms and Smart Order Routers. (Hendershott & Riordan, 2011)

With the fragmentation of financial markets, traders are now concerned in finding the best liquidity across multiple trading venues, while avoiding information leakage about their trade orders. Traders now use complex algorithms to hide their intentions in the market to avoid being front–run by HFTs with speed advantage. HFTs on the other hand try to find out the trading patterns and intentions in order to take advantage of it by using their speed advantage. This has led to a demand for anonymity in trading, resulting in an emergence of alternative trading platforms called dark pools. While dark pools may vary greatly in character (see Mittal, 2008 for classifications), they share the common interest in fulfilling the demand for anonymity. In dark pools, the order book is hidden so that traders do not see the placed orders, theoretically allowing the execution of large blocks instantly without fears of information leakage. Typically dark pools execute at the mid-point price, the mid-point of best bid and offer prices at primary exchanges and MTFs, so that both sides of the trade cross half the bid-ask spread regardless of the side of an order (to supply or to consume liquidity). However, dark pools have faced controversies and as discussed next, there are numerous problems associated with trading in dark pools as well.

Mittal (2008) argues that, contrary to general belief, dark pools are not completely safe from information leakage after all. If a trader completely fills his trade order in dark pool, it is reasonable to assume there is remaining liquidity in the dark pool, signaling a demand for a matching order. Dark pools typically leak information through practices of fishing and information sharing. Fishing is a gaming practice where other market participants try to manipulate dark pools by posting small orders to a dark pool to detect whether there is a large order sitting in the pool, providing information of hidden demand. Information sharing is a practice where a dark pool sells the entire information of an incoming trade order to a third participant for a fee, leading to information asymmetry and potentially major adverse selection. Traders try to avoid trading in these so–called toxic dark pools, but as all dark pools are different and there is scarcely any information available about them, measuring the dark pool toxicity could be a daunting task. (Mittal, 2008)

Dark pools have faced numerous controversies the past years. In 2016, Barclays and Credit Suisse were fined for $154 million by U.S. regulators for misleading investors about the safety of their dark pools while welcoming HFTs to game incoming orders (Moyer, 2016). While being the most recent, these scandals are not the only ones. In 2015, SEC fined UBS for not executing trades fairly in its dark pool (Chon, 2015). In 2011, Pipeline Trading Systems LLC was caught and sanctioned by SEC for using its own proprietary trading machine to execute against customers' trades to its own advantage (SEC, 2011). Similarly, Investment Technology Group Inc. was caught in 2015 for using knowledge of customers' information flow in advantage for its own proprietary trading (Robinson, 2015). The opaqueness and controversies surrounding dark pools has resulted in a tighter scrutiny by regulators.

The financial markets have evolved considerably the past decades. Before the emergence of computerized trading platforms, market makers made the markets by posting bids and offers for investors while gaining profits in the form of spreads. Even then various controversies surrounded these brokers as they got caught by doing something illegal, or barely legal, to scalp gains from investors. Over time, as the ECNs superseded the traditional floor brokers, overall market structure had a tremendous change. Spreads narrowed as investors traded directly against each other without middlemen taking their gains in the process.

Long before the MiFID or Reg. NMS changed the field of trading, there has been demand for anonymous trading. Forster and George (1992) show that an order placed by a big institutional investor is considered significant information and affects the stock prices. Some traders end up having private information which leads to increased adverse selection and increased trading costs due to increase in bid-ask spreads. They continue that in order to improve the markets, this information leakage needs to be attended to. Indeed, finally after the introduction of Reg. NMS and MiFID the competition in trading venues opened and venues called dark pools started to increase in popularity. However, as market participants have recently found out, full anonymity in order book is not necessarily a desirable trait.

In U.S. this began by the implementation of new SEC regulations. Reg. ATS and Reg. NMS ended the one-size-fits-all model of market design and opened the exchange market to new competitors. New trading venues were crafted to fulfill the needs of specific traders. This increased competition put pressure on the existing exchanges who responded by creating markets within markets, by setting up specialized market microstructures to attract specific market participants. This finally resulted in fragmented and extremely fluid markets. The venues now compete for trading volume and try to attract traders that bring volume into the trading venue. However, they need to attract the right kind of volume. By attracting toxic, predatory HFTs might scare the retail and institutional traders to trade in different venues if they find too much adverse selection in a given trading venue. (O'Hara, 2014)

Trading venues try to attract the right kind of order flow by making decisions regarding the market design. For example, in the electronic markets, liquidity arises from limit orders. A trader can make liquidity by submitting a passive order, which is a limit order to buy at bid or to sell at ask. Trader could consume liquidity by submitting an aggressive order. In this case, the aggressive trader crosses the spread and buys at ask or sells at bid. Exchanges typically attract liquidity by paying rebates to traders that provide liquidity, while the liquidity consuming orders have to pay a fee. This market design has become highly attractive to HFTs who can submit and cancel their limit orders before any other market participant due to their advantage in speed. The speed allows HFTs to minimize their risk as they are able to cancel orders if necessary. The rebates from limit orders has become a major source of profit for some HFTs. There are also other kinds of market designs. A take-maker market is the opposite of maker-taker model where the trader submitting a liquidity providing limit order has to pay a fee, while a trader submitting a market order receives rebate. (O'Hara, 2014) Ye et al. (2013) find that this market design is less attractive to HFTs. In subscription markets a market participant pays a fixed fee and can then trade as much as he wants. (See O'Hara, 2014)

Exchanges have also come up with different order types, some of which specifically catered for HFTs. BATS Exchange COO Chapman (2012) claim the number of different order types now amount to more than 2000 different order types, each crafter for specific purpose. For example, a Hide not Slide order is an order that allows traders to circumvent rules designed to prevent locked market situation where the bid equals ask. This has brought up complaints that it puts some traders at a disadvantage, while others claim it provides traders an enhanced ability to control the execution of their orders. When the market is locked, it does not unlock until orders slide to a worse price, creating the bid-ask spread. The Hide not Slide order allows the order to be hidden and not slide. When the market unlocks, this order reverts into a normal limit order but it has the advantage of being the first in the queue. (O'Hara, 2014)

A trade incurs information in a variety of ways. Things such as buy or sell orders, trade size, volume and time between trades all include information that some market participants seek to exploit. The algorithmic trading has not changed the story, but the rules have changed. Now a singular trade does not include much information – the information lies in the underlying orders. Haldane (2012) claims that adverse selection has changed the past years. In a high speed, co-located world, being informed means being faster than others. Now it pays to be faster, not smarter. Being uninformed means being too slow. O'Hara (2014) points out that while speed being synonymous with informed trading is not the whole story, it highlights the complexity of information in the high–frequency age. He continues that informed trading is multidimensional, meaning that traders can use information to take advantage of liquidity providers. Some markets and data providers sell access to public information seconds or milliseconds before making the information public (see e.g. Easley et al. 2013). This practically turns public information into private information. Co-location allows HFTs to better predict and see market movements than other traders. This also makes them informed traders. O'Hara (2014) argues that these expanded definitions of informed trading are worrisome. He claims that now it is not anymore clear what drives the adjustment of price or where they are going. On the other hand, analyses of market efficiency suggest that markets remains informationally efficient despite these new changes. But markets are now characterized by episodic instability. Informed high–frequency market makers flee the markets by cancelling their orders when they suspect that other, more informed traders are present. In addition, markets are now more inter-connected, sewn together by traders using market making and statistical arbitrage strategies that operate across, not just within, markets. (O'Hara, 2014)

2.3 Transaction costs

In addition to the increased complexity in trading environment, the trade execution as a process has also seen significant changes. Most traders seek to optimize the trading strategies and algorithms to minimize or hide the signal they would create with their orders. The speed and timing of execution has also become increasingly more important as the new market structure has allowed for new kind of predatory trading. Moreover, the client order execution of investment firms have been put under tighter scrutiny as a result of MiFID's obligation for best execution which obligates investment firms to *"take all reasonable steps to obtain the best possible result for their clients"* (CESR, 2007). As a result, the pressure to perform more efficient execution has naturally increased.

Transaction costs are widely recognized as a large driver of investment performance (see e.g. Freyre-Sanders et al. 2004; Obizhaeva and Wang, 2013). Transaction costs affect the realized returns of an active investment strategy and control how rapidly assets can be converted into cash. Improving trading execution is associated with improving the trading algorithms that slice parent order into smaller batches in order to hide the signal generated by the order while executing trades at the best possible prices. Over the past years, algorithmic trading has become widely adopted and now most of the institutional traders use trading algorithms bought from sell-side investors or build their own algorithms. The reasons for the fast spread of trading algorithms can be found on the changes in market structure, cost, efficiency, and the need for best execution (Garcia, 2005). Traders typically monitor the impact, slippage, adverse selection and price reversion of their trades. These attribute to the overall trading execution performance. Although the costs of singular trades can seem minimal, the accrued costs can be very high and is one of the reasons mutual funds, for example, lose to their benchmark indices. (Ferreira et al., 2012)

When investor makes a choice between a limit order and a market order, he weighs the trade-off between more favorable price and liquidity. As stated, market order is liquid and executes with the best limit order in the order book, while a limit order trades at a more favorable price but is more illiquid as there is no guarantee that someone is willing to cross the spread to execute with this limit order. A buyer (seller) pays a premium, or liquidity cost, for immediacy defined between the average price of executed market order and the best bid (ask) limit order price. The liquidity costs of market orders are a function of transaction size. As the market order depletes the order book in a decreasing order, starting from the best ask (bid) price, a large market order placed on the order book widens the bid-ask spread and pushes the price towards more unfavorable levels as it moves through different limit orders. Dark pools are used to find the middle ground between passive and aggressive orders. Traders could favor these dark pools as they provide anonymity and execution at midpoint price saves half the spread when compared to aggressive trades in lit markets.

Bessembinder (2003) finds that quoting competitiveness has an impact to ex-post execution costs in NYSE-listed stocks. He shows that Nasdaq Intermarket execution costs tend to be higher when its quotes are not competitive and further notes that when quotes are competitive, the differences in execution quality are negligible. Bessembinder's findings suggest execution costs vary among markets and over time. It raises the question whether participants consider such variations when making order-routing decisions. Because of data limitations, it has been difficult to answer to this question. Boehmer et al. (2006) try to answer this question by focusing on how routing decisions respond to variation in execution quality at different market centers. Boehmer et al. (2007) present an econometric model for order-routing behavior for marketable orders in NYSE-listed stocks and test whether an execution venue's market share, the outcome of brokers' routing decisions, is related to past execution quality. They use round-trip effective spreads and execution speed to measure the execution quality of the trading venue. Effective spread can be decomposed into two parts: permanent and temporary component. Temporary component is the realized spread and it excludes the effects of the information content on order flow. To gauge the temporary component, they define realized spread as twice the (negative) difference between the execution price and the NBBO (U.S.) or EBBO (Europe) quote midpoint five minutes after the trade for buy (sell) orders. The permanent component, on the other hand, is defined as the price impact. It is the change in the quote midpoint from order receipt to five minutes after execution, or half the difference between effective and realized spreads. The permanent component is used as an approximation to the information component of an order. Execution speed is the time between an order receipt and execution.

2.3.1 Implementation Shortfall

Perhaps the most widely used measure for trading costs is the implementation shortfall (referred also as slippage), first described by Perold (1988). Slippage measures the volume-weighted average trade price (or VWAP) for an investor's order to a reference price such as quote midpoint at the time of the trading decision. Slippage is simply the difference between a theoretical entry price and the actual fill price. Entry price is the price of an asset when trading begins or when trader receives an order from the portfolio manager. Actual fill price is the price at which the trader has finally executed an order. Because of the negative effects of slippage, even profitable trades could turn into losses if the slippage turns out to be too large. For example, consider a trend-following momentum strategy with stop orders. Stop order triggers when the underlying asset price reaches certain levels. If the asset price is rising and goes through the stop order price, the trade generates slippage losses as the trader pays more for each trade during the surge. The same applies when asset price is falling through the stop order price. As stop orders inherently result in high slippage, traders could use stop-limit orders instead to minimize slippage at the cost of missing trade opportunities. In this case the trader is not executing at unfavorable prices during a momentum change. On the other hand, using a limit order the trader could miss trading opportunities when no one is hitting his price offer anymore.

Slippage shows what happens during the execution of an order. Institutional investor naturally could not execute its trade order instantly without causing major price impact. Rather, he slices the parent order into numerous small child orders, each executed independently, thus reducing the price impact of an order. However, with the current market structure an issue arises if the trade order is detected by other market participants, such as HFTs, and is taken advantage of. If HFT trades against an investor's order, HFT provides liquidity to meet the investor's demand. However, HFT could take advantage of this demand by trading at the same direction than the investor, where HFT races ahead of the investor in order book to execute before him only to later sell (buy) the shares in demand at the higher (lower) price (Brogaard & Hendershott, 2014).

When placing a limit order, a singular trade is immune to slippage. However, the trading execution is viewed from the viewpoint of parent order consisting of numerous smaller trades. For example, if a trader wants to buy 10 000 shares of Apple, he would slice it into small trades of 100 shares each to minimize market impact and hide his intentions. However, the trader obviously could not execute all of these small trades at the same price. The slippage can be positive or negative, positive slippage meaning additional profits gained from trading at more favorable prices and negative slippage is the additional costs for trading at less favorable prices. In the current trading environment, characterized by HFTs and fragmented markets, other market participants are seeking for these trades and try to profit at the expense of the trader trying to fill his order. Because of the changed environment, slippage is now typically always negative and traders try to minimize it as much as possible by using different trading strategies.

Implementation shortfall, first presented by Perold (1988) is measured as the difference between the paper return and the portfolio return. In paper return, all shares are assumed to transact at the prevailing market prices at the time of the investment decision. Mathematically, this is written as:

$$IS = Paper\ Return - Real\ Portfolio\ Return \tag{1}$$

To better understand how these transaction costs affect portfolio returns we consider three cases of IS: i) all shares transacted in complete execution ii) incomplete execution where the investor incurs opportunity cost, and iii) incomplete execution. Kissell (2006) differentiates incomplete execution into trading related, investment related, and opportunity cost (expanded implementation shortfall). In the case of complete execution, we can write the equation as follows:

$$\begin{aligned} IS &= (S * P_N - S * P_d) - \left(S * P_N - \textstyle\sum s_j p_j\right) - fixed \\ &= \textstyle\sum s_j p_j - SP_d - fixed \end{aligned} \tag{2}$$

where, s_j is the number of shares executed in the j^{th} transaction, $\sum s_j$ is the total number of shares executed, p_j is the price of the j^{th} transaction, and $\sum s_j p_j$ is the total transaction value (e.g., cash invested). The fixed[4] function of the formula presents the costs that are not dependent on the trading strategy, such as commissions, taxes, clearing and settlement fees, etc. S, $s_j > 0$ indicates a buy order and S, $s_j < 0$ indicates a sell order. In the case

[4] In this thesis, the fixed transaction costs are excluded from the research. It is nearly impossible to reduce the fees of trading as a buy-side investor and fixed costs have no effect on the results or plausibility of this study.

where all shares are executed the implementation shortfall is simply the total transaction value minus the value at the time of the investment decision minus fixed costs. It is not dependent on the future stock price P_N.

In the case of incomplete execution, where the order is not entirely executed, we have to take the opportunity cost into account. The formula is as follows:

$$IS = \underbrace{\sum s_j\, p_j - \left(\sum s_j\right) P_d}_{\text{Execution Cost}} + \underbrace{\left(S - \sum s_j\right)(P_N - P_d)}_{\text{Opportunity Cost}} - fixed \qquad (3)$$

In this case, the ending value of the portfolio equals the total number of shares executed at the stock price at the end of the trading horizon plus the amount of cash not invested in the portfolio. This implementation shortfall, defined by Perold (1988) distinguishes between execution cost and opportunity cost of the order. The execution cost component in equation (3) spans two time horizons: investment and trading. The investment time horizon is the time period from investment decision t_d to the time when trading begins t_0. The trading horizon is the time period of trade execution from when the trading begins t_0 to the end of trading t_n.

Finally, we formulate the expanded IS, first proposed by Wagner and Edwards (1993). The expanded IS makes a further distinction between the investment and trading horizons and further highlights the specifying of appropriate execution strategy. The formula of expanded IS goes as follows: (See e.g. Almgren & Chriss, 2000; Kissell & Glantz, 2003; Rakhlin & Sofianos, 2006)

$$Expanded\ IS = \underbrace{S(P_N - P_0)}_{\text{Investment Related}} + \underbrace{\sum s_j\, p_j - \left(\sum s_j\right) P_d}_{\text{Trading Related}} + \underbrace{\left(S - \sum s_j\right)(P_N - P_0)}_{\text{Opportunity Cost}} - fixed \qquad (4)$$

As depicted in equation (4), transaction costs can be divided into three main categories: Investment related, trading related and opportunity cost. The investment–related costs arise during the investment decision phase and mainly constitutes from the potential lack of communication between portfolio managers and traders in deciding the proper implementation strategy or due to a delay in selecting the appropriate broker, algorithm, or algorithmic parameter. The time spent in this phase exposes the investment to adverse price movement, ultimately making the investment more costly. The trading–related costs account for most of the total trading costs and include the costs arisen during the implementation of the investment decision, duration. Duration is the time period from the start of trading to the end of trading. These costs cannot be completely eliminated but can be managed by using an appropriate execution strategy. Trading-related costs have two main components: Market impact and timing risk. There is a trade-off between these two cost components as market impact increases when using more aggressive trading strategies, while passive trading strategies cause less market impact in markets. On the other hand, the timing risk can be mitigated by using more aggressive trading strategies as there is less time for the stock's adverse price movement. Opportunity cost represents the foregone profit or loss resulting from not being able to fully execute the order within given time period. Opportunity costs typically arise from the fact the trader is unwilling to execute at prevailing market prices or because of insufficient market liquidity. (Kissell, 2006) This thesis mainly focuses on trading-related costs.

2.3.2 Transaction cost categorization

The total financial transaction cost consists of fixed and variable costs and includes both visible and hidden fees. Fixed cost components are costs that are not dependent on the implementation strategy as they cannot be managed during the implementation phase. Variable cost components vary during the investment decision phase and are dependent on the underlying implementation strategy. Variable cost components account for most of the total trading costs and are the main concern of traders. Visible costs are the costs with a transparent fee structure that is known in advance. Visible costs are mainly attributable to commissions, fees, spreads, and taxes. Hidden costs, on the other hand, are the non–transparent costs such as market impact costs that cannot be known until the order is executed. Statistical models are used to estimate the hidden costs, though precise estimation is impossible. The hidden variable costs account for most of the total trading costs and provide the greatest potential for performance enhancement. Hidden variable costs can be the decisive force that decides whether the investment is profitable or not. (Kissell, 2006) Because of these reasons, hidden variable costs are the biggest concern for traders and portfolio managers. As a result, this thesis will focus on the hidden variable costs as well

In order to gain deep understanding of the transaction cost structure in trading, one needs to be able to distinguish and differentiate the transaction cost components. Kissell (2006) categorized the transaction costs into nine components:

1. Commission – Payment made to broker-dealer in exchange for trade execution. Typically expressed as per share basis or based on total transaction value. Commissions fall under the fixed and visible transaction cost components category.

2. Fees – Fees include various fixed costs such as exchange fees, SEC transaction fees and clearing and settlement costs. Brokers typically bundle these costs into commissions. Like commission costs, fees fall under the fixed and visible transaction cost components category.

3. Taxes – Levy assessed based on realized earnings. Tax rates vary by investment and type of return. Tax rates are known in advance but the realized tax costs are now known until the final transaction prices are known. Taxes fall under visible variable cost components category.

4. Spreads – The bid-ask spread is intended to compensate broker-dealers for matching buyers with sellers and for the risks associated in being passive such as acquiring and holding stocks while waiting for someone to cross the spread in order to unwind the position. Spreads correctly represent the round-trip transaction costs for small orders but do not accurately enough for larger trade blocks. Spreads can be observed from the market at any time and they may vary during the day. Spreads fall under visible variable cost components category.

5. Delay Cost – Represents the adverse price movement between the time when the manager makes the investment decision t_d and the time the order is released to the market t_0. Buying rising stocks and selling falling stocks incurs delay costs. Any delays in order submissions in these situations will result in adverse price movement, leading to less favorable execution prices and higher transaction costs. There are various reasons that can attribute to delay costs. For example, trader may incur delay costs if he hesitates in releasing the order to the market. Second, delay cost may arise due to the uncertainty in finding the most capable brokers (or algorithms) for the particular orders. Third, incorrect anticipation of market direction could expose the order to high delay costs if the adverse

trend movement persists. Fourth, unintentional information leakage may substantially increase the total transaction costs because other market participants can take advantage of the order being released[5]. Fifth, the change between previous day's close and next day's opening prices may result in delay costs. Delay costs fall under hidden and variable cost components category.

6. Price Appreciation – Also referred as price trend, drift, momentum or alpha. Represents the costs (savings) associated with buying stock in a rising (falling) market or selling (buying) in a falling (rising) market. Price appreciation falls under hidden and variable cost components category, it is dependent upon the stock trend and used implementation strategy.

7. Market Impact – Represents the adverse movement in the stock price caused by a particular trade or order. Market impact is one of the main drivers of total transaction costs and it has two main components: i) the liquidity demands of the investor, and ii) the information content of the order. The liquidity demand simply means that the investor willing to trade stocks needs to add a premium in order to attract more liquidity into the market. For buys this means that the investor would need to add a premium to its price and for sells the investor has to sell at a discount. The information content of the trade is the signal sent to the market whether the stock is believed to be under- or over-valued. Market impact is dependent on size, volatility, size of transaction, prevailing market conditions (i.e. current market liquidity and intraday trading patterns) and implementation strategy used. Market impact falls under hidden variable cost components category.

8. Timing Risk – Refers to the uncertainty surrounding the estimation of transaction costs. Price volatility and liquidity risk are factors of timing risk: price volatility will cause the stock price to be higher or lower than the estimated price due to forces independent of the order and liquidity risk has a direct effect on the magnitude of market impact caused to the stock price. The liquidity part of timing risk is dependent upon volumes, intraday trading patterns, and cumulative market impact cost caused by other market participants. Timing risk falls under hidden variable cost components category.

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[5] The problem of information leakage has grown substantially as proprietary HFTs use sophisticated methods, such as "pinging" in finding the underlying order blocks behind singular orders and trades (see e.g. Wald, 2011; Aitken et al., 2012)

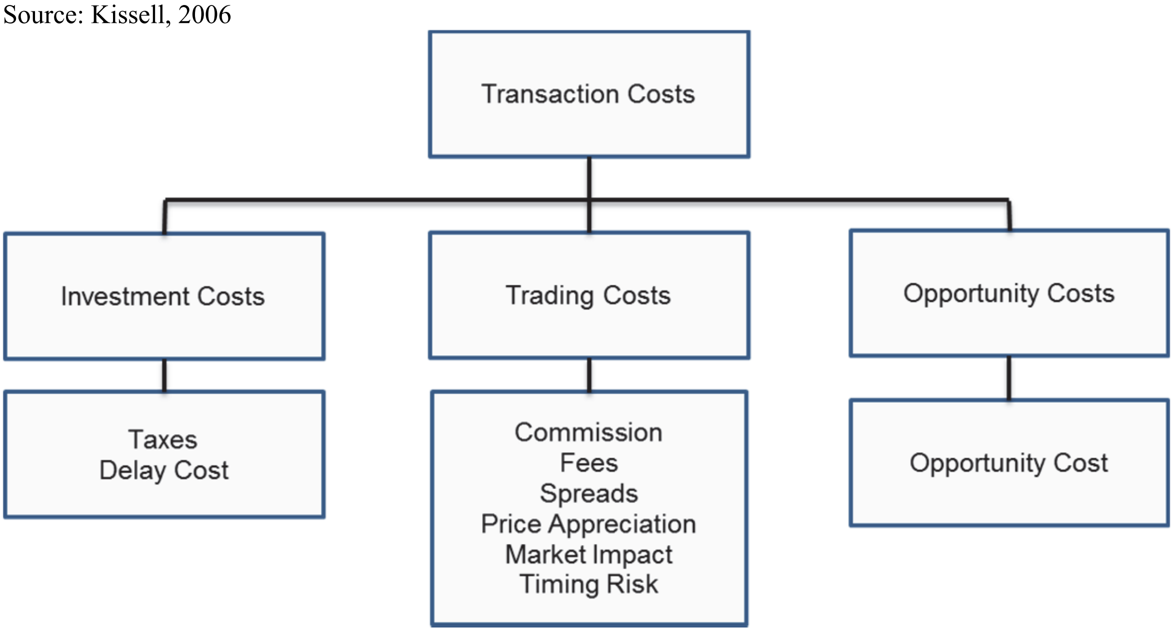
9. Opportunity Cost – Represents the losses caused by the inability to fully execute the investment decision. It is usually due to insufficient liquidity, adverse price movement or a combination of both. Opportunity cost also falls under hidden variable cost components category. (Kissell, 2006)

The categorization of nine transaction cost components discussed is shown in Table 2. As can be seen from the table, most of the transaction costs fall under the category of hidden variable transaction costs. It is both good and bad news for investors at the same time. There is a huge potential to minimize the variable costs and increase profits by using sophisticated tools and implementation strategies. On the other hand, the fact that the cost structure is non-transparent, poses problems to investors because it is difficult to develop accurate transaction cost models.

Table 2: Transaction cost categorization. Source: Kissell, 2006

	Fixed Costs	Variable Costs
Visible Costs	-Commission -Fees	-Spreads -Taxes
Hidden Costs	n/a	-Delay Cost -Price Appreciation -Market Impact -Timing Risk -Opportunity Cost

Table 3: Breakdown of transaction costs into three dimensions of expanded implementation shortfall. Source: Kissell, 2006



As shown in Tables 2 and 3, a negative slippage is the sum of many variables. One of the biggest factors for negative slippage is the market impact. Buying an asset pushes the price upwards and selling pushes the price downwards. An aggressive order crosses the spread hitting a passive limit order, moving the asset price towards more unfavorable levels. In other words, aggressive orders increase slippage losses of the parent order. Predatory HFTs have an impact on the overall slippage as well. If these high-speed computer algorithms find out that there is a larger parent order behind singular trades, the HFT may take advantage of this situation. While theoretically the market impact could be zero by exclusively using limit orders, traders cannot use this strategy as they have to execute the parent orders in order to follow the pre-defined strategy of a mutual fund or investment portfolio. (Kissell, 2006) As a result, the trading execution is balancing between minimizing slippage and seeking liquidity in order to execute the parent order. Bohn (2011) suggests that the act of buying or selling does not change prices. Instead, the change comes as a result of competition for liquidity among buyers and sellers.

Similar to Kissell (2006), Bohn (2011) defines slippage as the sum of *cost of waiting* and *fluctuations in supply and demand.* The cost of waiting illustrates the losses accrued between the time of investment decision and order execution, while fluctuations in supply and demand represent the price change and the imbalance of the outstanding buy and sell volumes. If the majority of orders are placed in sell side of an order book, the combined masses cause a pressure for the asset price to decrease.

Bohn (2011) finds positive skewness in slippage that can be explained by an average price increase as a function of the buy-sell imbalance. He further finds a positive correlation between negative slippage[6] and execution time, indicating that the duration of an order leads to higher transaction costs. Consider a simplified example where there are numerous buyers and only one seller. Due to a positive price pressure, the seller will profit from the price increase and execute his order quickly because of the weak competition among sellers. Buyers compete for the liquidity provided by sellers and in aggregate suffer from the price increase and increased liquidation time caused by the competition. This is a small

[6] Contrary to most scientific studies, Bohn (2011) uses positive slippage as a proxy for transaction costs, while negative slippage acts as a proxy for transaction savings. Like Perold (1988) and most other researchers, I will use positive slippage as a proxy for transaction savings and negative slippage for costs.

gain for the minority and a larger loss for the majority. The study concludes that the slippage is intrinsic to trading seen as a negotiation process between agents.

3. Research questions and hypotheses

This chapter presents the hypotheses of this thesis. All of the hypotheses reflect the measurement of realized transaction costs under different market conditions. The hypotheses focus on two key factors: Implementation Shortfall (IS, Slippage) and Price Reversion. My first hypothesis relates to the possible connection between market liquidity and transaction costs. The second hypothesis relates to finding a connection between market volatility and transaction costs.

Perold (1988) defines Implementation Shortfall as *"the difference in return between a theoretical portfolio and the implemented portfolio"*. This difference is also called slippage. A positive slippage indicates that the trading was successful in that the investment was made in more favorable price than at the time when the decision was made. On the other hand, a negative slippage indicates that there has been an unfavorable price development, leading to trade execution at worse price than it was at the time the decision was made.

A number of factors affect the final, realized price of an order in contrast to its initial notional value. Kissell (2006) divides the transaction costs into three main categories: Investment-related costs, trading-related costs and opportunity cost. He further defines nine components that drive the transaction costs: commissions, taxes, fees, spreads, delay cost, price appreciation, market impact, timing risk, and opportunity cost. I leave commissions, taxes and fees outside of this study and rather focus on the real drivers of slippage.

These components form the background for research questions and hypotheses used in this study.

Therefore,

Research question 1: Does stock liquidity have an effect on trading costs?

The research question 1 includes two null hypotheses:

H0: There is no evidence of association between stock liquidity and implementation shortfall.

H0: There is no evidence of differences in price reversion mean values under different stock liquidity conditions.

Liquidity is a key driver of transaction costs. If the order book is thin, in that the order book has insufficient bids and/or offers, a possible trade would most likely go through different bid (offer) levels, increasing market impact and transaction costs. In this thesis, liquidity demand is described as trade order's volume to average daily volume ratio (%ADV). The average daily volume is calculated for all venues and averaged over 30 days. The bigger the investor's share of the average total volume, the more liquidity is being consumed.

Research question 2: Does market volatility have an effect on trading costs?

The research question 2 also includes two null hypotheses:

H0: There is no evidence of association between market volatility and implementation shortfall.

H0: There is no evidence of differences in price reversion mean values under different market volatility conditions.

The underlying assumption is that higher volatility leads to disturbances in the market microstructure, leading to higher transaction costs. Earlier studies conclude that volatility affects the bid-ask spreads of assets being traded (see e.g. Demsetz, 1968; Tinic and West, 1972; Tinic, 1972; Benston and Hagerman, 1974; Hamilton, 1978; Copeland and Galai, 1983) and bid-ask spread, among other factors, are known to have an impact on transaction costs.

The research questions and null hypotheses of this thesis are summarized in a Table 4 below and in the introduction chapter (Table 1).

Table 4: Research questions and null hypotheses

Topic	Research Question	Null Hypothesis (H0)
Market conditions and implementation shortfall	Do the market conditions have an effect on implementation shortfall?	1. H0: There is no evidence of association between stock liquidity and IS
		2. H0: There is no evidence of association between market volatility and IS
Market conditions and price reversion	Do the market conditions have an effect on price reversion?	3. H0: There is no evidence of differences in means of price reversion values under different stock liquidity conditions
		4. H0: There is no evidence of differences in means of price reversion values under different market volatility conditions

Followed by the market fragmentation, high-frequency trading has revolutionized the equity markets and changed the transaction cost structure of investors. Even though HFT plays a major role, I do not study their role in markets directly. Rather, I study HFTs indirectly by analyzing the transaction costs of a Finnish Asset Management firm.

4. Methodology and data

This chapter introduces the methodology and data used to study the slippage and price reversion under different liquidity and volatility conditions. In addition, main limitations of this thesis are discussed.

4.1 Methodology

This research focuses on finding evidence of significant differences in adverse price movement during the duration of an order under different stock liquidity and market volatility conditions. Slippage, also called implementation shortfall or IS, is used to analyze the trading performance. Parent orders are first analyzed as a whole and then buy and sell orders separately. Slippage is a widely used quantitative metric in analyzing trade execution performance (see e.g. Dempster et al., 2001; Dodds, 2015). In addition, the price movement after an order fill is examined by measuring post-trade prices at various time intervals. Post-trade price movement analysis is done by analyzing price reversion, which is also a widely used quantitative metric for trade execution performance evaluation (see e.g. Huberman and Stanzl, 2005; Saraiya and Mittal, 2009; Dodds, 2015).

Average Daily Volume (ADV) is a direct indication of a security's overall market liquidity and in describing liquidity demand, parent order's volume to Average Daily Volume ratio is chosen. The higher the order size relative to the average daily volume is, the more liquidity is being consumed. Average daily volume is the average volume for all venues, averaged over 30 days. In this study, the liquidity demand is split into four different categories: low, moderate, medium-high and high. Low liquidity demand category includes all orders with liquidity demand from 0% to 0.44%, moderate liquidity demand from 0.45% to 0.93%, medium-high liquidity demand from 0.94% to 1.99% and finally high liquidity demand includes all orders with 2% and more liquidity demand from average daily volume.

Volatility risk is an important factor for traders to take into account when selecting appropriate execution strategy. Almgren (2012) presents optimal trading strategies for different volatilities in detail. In short, his proposition is to execute trade order quickly in volatile times and more slowly when the market volatility is low. In this thesis, market volatility is chosen to describe general market uncertainty on daily basis. To describe market volatility, Euro Stoxx 50 volatility (V2X) index is chosen. Using volatility of European large-cap stock markets as a proxy for volatility in Finnish large-cap stock markets is warranted due to the high level of integration in Euro area and spillover effects, which are extensively investigated phenomenon (see e.g. Ehrmann et al., 2011; Diebold and Yilmaz, 2012). Based on this strong theoretical and empirical background, I make the assumption that the volatility in OMXH25 stocks is similar to the volatility in Euro Stoxx 50 stocks. In this thesis, the market volatility is split into three, equally large bins. Low volatility includes range in volatility from 12.713 to 18.5097 index points, normal volatility includes the range from 18.5935 to 22.5806 index points, and finally high volatility includes volatility range from 22.7637 to 40.803 index points.

As in previous, similar studies (see e.g. IFS, 2013; Toulson, 2013), the European best bid and offer (EBBO) mid-price is used as a definition of a stock price. In this thesis, The EBBO mid-price is defined as the best bid and offer prices that are available in the Helsinki Stock Exchange (OMXH) and four European Multilateral Trading Facilities (MTFs), which are Chi-X Europe, BATS Europe, Burgundy and Turquoise. The best bid price is the highest available bid price and the best offer price is the lowest available offer price in these aforementioned trading venues.

The implementation shortfall (IS) formula first presented by Perold (1988) is used to examine slippage of individual trades. This is done by calculating the difference between the stock price at the time of arrival and the realized weighted average execution price. The original implementation shortfall formula is as follows:

$$IS = \frac{((Q_A * P_A) - (\sum_{i=m}^{n} Q_i * P_i)) * S}{Q_A * P_A} * 10000 \tag{5}$$

Where
Q_A = Executed order quantity
P_A = Price at the time of arrival
Q_i = Quantity of an individual fill
P_i = Price of an individual fill
S = Denotes the side of the trade. In buy orders S = 1 and sell orders S = -1
$\sum_{i=m}^{n} Q_i * P_i$ = The achieved market value of an order
Formula is multiplied by 10 000 so we get results in basis points (BPS)

The implementation shortfall formula above can be simplified to the following:

$$IS = \frac{(P_A - \bar{P}_E) * S}{P_A} * 10000 \quad (6)$$

Where
$\bar{P}_E$ = Average trade price of an order

Which can also be expressed as:

$$IS = \frac{(Arrival\ price - Average\ price) * S}{Arrival\ price} * 10000 \quad (7)$$

In buy (sell) orders, if the arrival price is higher (lower) than the average price, a trader has been able to fill an order with a better price than a decision price (the price the moment the investment decision is made). All orders have been normalized to buy orders in order to get comparable results.

In analyzing adverse selection, researchers typically use very short periods of time to see what happens immediately after the order fill (see e.g. Huberman and Stanzl, 2005; Saraiya and Mittal, 2009; Dodds, 2015). This is essential when examining what happens right after the order fill, especially in the modern, algorithmic-driven trading environment with the concerns of predatory high-frequency trading. However, as Agatonovic et al. (2012) mention, longer time periods can also be used in post-trade price movement analysis. In this study, I use the time periods of 1, 5, 10, 15, 30 and 60 minutes after the order execution and the closing price of the day. This is done in order to be able to more precisely evaluate both the temporary and permanent price impact of an order. These time periods are common when conducting transaction cost analysis (TCA) and post-trade price movement. The chosen time intervals are also the default time periods used by IFS in Liquidmetrix TCA analysis tools. The time intervals of 1, 5, 10 and 15 minutes express the temporary price impact and time intervals of 30 and 60 minutes after order fill and the closing price of the day represent the permanent price impact with the expectation that the temporary price impact has been dissipated. In analyzing the post-trade price movement in relation to average trade price, EBBO mid-price is used in the chosen time intervals.

The slippage and price reversion observations have been averaged by an arithmetic mean to get the average slippage or price reversion under different market conditions. Then t-tests are run in pairs to test if the differences of averages in slippage or price reversion are statistically significant under different market conditions. T-tests are run in pairs since the aim is not only to test the level of slippage or price reversion under certain market conditions, but also to test the magnitude and significance of differences in the respective results. By conducting t-tests in pairs, it is possible to analyze whether there is a significant difference when market conditions are almost similar, or when the conditions are totally the opposite. In addition, Kendall's tau nonparametric test is used to examine how the execution performance correlates with market conditions.

4.2 Data

The stock price development during and after an order fill is examined by using unique trading data of a Finnish Asset Management company. In this thesis, I focus on parent orders during the time period of 2.5.2014 – 30.10.2015. The time period is carefully chosen so that there were no major changes in trading algorithms which could distort the comparability of results. In total, the data consists of 4508 individual fills in the given time period. All orders are in OMX Helsinki 25 (OMXH25) stocks. The number of stocks traded range from 250 to 2,000,000 shares.

The trading data was gathered by using Intelligent Financial Systems' (IFS) Liquidmetrix Worksation's trade analysis tool. The original data set I started to work with comprised of 5039 individual orders. From this data set, I removed orders based on a few criteria: First, the trade had to be executed by using one of the more common trading algorithms as the more exotic algorithms are mainly used on special occasions only. At least 80% of the parent order has to be filled to be included in this study that focuses on analyzing the parent order performance. Some orders did not have sufficient data for the analysis and were excluded from this study. In addition, few significant outliers were excluded to make the analysis more feasible. Most of the trades were executed by using both lit markets and dark pools as a result of trading algorithm actively looking for the best price and liquidity in a set of venues. The European volatility index (V2X) data was gathered from

Bloomberg terminal's historical prices table from the same time period. The volatility index is used to describe the market volatility and is split into three equally large bins.

The descriptive statistics of the overall data is presented in Table 5 below. In the overall data, the average *duration* of a parent order is slightly above 30 minutes. The average *shortfall* of all trades is -16.1827 basis points indicating that, on average, a trader incurs losses of 16.1827 bps (or 0.1618 %) of the order's market value when executing a trade. *Participation VWAP 10* is used as a benchmark for order executions. It measures what would be the probable realized implementation shortfall if the order was executed at continuous ten percent market participation rate. *Average Daily Volume (%)* is the ratio the order quantity represents of the average daily volume in all venues, averaged over the last 30 days. In this study, the Finnish asset management firm accounts for 1.67 % of trading volume on average. Later this variable is used to find out whether it has an effect on slippage. *Market participation rate* is the executed quantity to the total market volume ratio for the duration of an order. In this data set, the company has an average of 61.42 % market participation. In other words, on average, the company accounts for more than a half of trading volume in a given stock while executing an order. The average in market participation rate is unusually high because some parent orders were filled very quickly when liquidity was found. For example, if a trader finds good liquidity in a dark pool, he can execute the whole parent order there, resulting in high market participation rate values. For example, the maximum value in market participation rate is 27,777.78 % and it is executed quickly in a dark pool. The median in market participation rate is 30.76%.

Primary participation rate is similar to market participation rate with the exception that primary participation rate calculates the executed quantity versus the market volume in a primary venue. The mean primary participation rate of 118.2 % indicates that the company tends to actively use dark pools to execute their orders. The median in primary participation rate is 46.55 % and the maximum value of 142,857.1 % is caused by the same trade which caused market participation rate to jump to 27,777.78 %. Traded on primary ratio tells us how big proportion of the trade execution has, on average, been executed on a primary venue. The mean of 61.89 % implies that, on average, most of the fills still happen on a primary venue, OMX Helsinki. The maximum of 100 % and minimum of 0 % indicates that some trades have exclusively been executed on a primary venue or alternatively on a dark pool or an MTF. *Volume traded* is simply the number of shares traded, the average volume of an order is 34 066 shares but the orders range from 250 to 2,000,000 shares. *Number of fills* tells us how many child orders a parent order is broken down into. On average, a parent order is broken down into 52 child orders. Some trades have been executed as a whole in one fill and one has been split into as many as 818 individual child orders. *V2X volatility* is the Euro Stoxx 50 Volatility Index, presented in index points. Later in this thesis it is used to examine whether volatility has an effect on trade execution performance.

Table 5. Descriptive statistics of the overall data. N=4508

	Mean	Median	Maximum	Minimum	Std. Dev.
Duration	30:28,7	13:30,8	8:11:11	00:00,0	52:07,6
Implementation shortfall (Bps)	-16.18	-7.71	205.65	-392.88	32.41
Participation VWAP10 (Bps)	-2.91	-0.76	264.52	-284.32	21.52
Average Daily Volume (%)	1.67	0.93	38.76	0	2.37
Market Participation (%)	61.42	30.76	27777.78	0.57	443.58
Primary Participation (%)	118.2	46.55	142857.1	0.85	2150.76
Traded on Primary (%)	61.89	68.58	100	0	27.04
Volume Traded	34066	12916	2000000	250	105491
Number of fills	52	36	818	1	58
V2X Volatility	21.38	20.61	40.8	12.71	4.94

In Table 6 below, implementation shortfall (IS) is categorized by volatility and liquidity conditions. As can be seen from the table, trades executed in low volatility and low liquidity demand conditions have the lowest implementation shortfall, indicating better performance in trade execution. On the other hand, the average in implementation shortfall is highest when trades are executed under high market volatility and liquidity demand conditions. These initial descriptive results show the existence of major differences in slippage under different market conditions and so indicate that both market volatility and liquidity demand might have an effect on the trade execution performance. However, the results are not linear as can be seen in low liquidity demand – normal volatility situation, where the slippage is in fact higher than in low liquidity demand – high volatility situation. Also the slippage is higher when market volatility is normal and liquidity demand is low compared to slippage of trade executions when market volatility is normal and liquidity demand is moderate.

Table 6. Implementation shortfall in different volatility and liquidity demand conditions.
Liquidity demand is split into four and market volatility into three subcategories, so that each category have close to equal amount of observations. Liquidity demand is split so that low category is liquidity demand with 0%-0.44%, moderate 0.45%-0.93%, medium-high 0.94%-1.99% and high 2%+.

Liquidity demand (% of ADV)		Market volatility: Low	Normal	High	All
Low	Mean	-7.51	-10.39	-7.65	-8.47
	Std. Dev.	13.48	17.43	16.47	15.88
	Obs.	387	356	388	1131
Moderate	Mean	-12.77	-9.87	-14.59	-12.5
	Std. Dev.	19.43	29.26	25.73	25.36
	Obs.	337	368	421	1126
Medium-high	Mean	-18.73	-21.2	-19.99	-20
	Std. Dev.	29.84	36.83	37.1	34.8
	Obs.	363	390	370	1123
High	Mean	-20.56	-23.47	-28.35	-23.79
	Std. Dev.	34.89	45.02	52.94	44.22
	Obs.	417	389	322	1128
All	Mean	-15.02	-16.46	-17.08	-16.18
	Std. Dev.	26.64	34.55	35.32	32.41
	Obs.	1504	1503	1501	4508

The later parts of this thesis focus on finding conclusive evidence on how trade execution performance is affected by volatility and liquidity.

4.3 Main limitations

Despite the fact that the data used in this study is very unique and allows more thorough studies compared to public data, it has its limitations. Perhaps the biggest limitation of this study is the generalizability of the results. The asset management company in question has invested a lot of time and effort to optimize their trading strategies, including sophisticated trade performance analytics tools also used in this study. As a result, the dataset used in this thesis might completely miss the most toxic dark pools and adverse selection caused by some predatory trading algorithms.

5. Results

In this chapter, the empirical results of this thesis are discussed. This chapter will progress as follows. First, in chapter 5.1 the implementation shortfall (slippage, IS) is analyzed under different stock liquidity and market volatility conditions. Chapter 5.2 examines the price reversion occurring after an order fill under aforementioned stock liquidity and market volatility conditions. In both cases, the order fills are first analyzed as a whole and then buy and sell orders separately. Chapter 5.3 examines the differences between buy and sell orders under the market conditions discussed. In this thesis, the order fills represent the completion of parent orders. Lastly, chapter 5.4 discusses the main results of the thesis.

5.1 Implementation shortfall under stock liquidity and market volatility conditions

In this chapter, implementation shortfall (also referred as slippage or IS) is analyzed under different liquidity and volatility conditions. Average Daily Volume (ADV) is a direct indication of a security's overall market liquidity and to describe liquidity demand, parent order's volume to Average Daily Volume ratio is used. The higher the order's share of the average daily volume is, the higher the demand for liquidity. The liquidity demand is split into four different categories: low, moderate, mediumhigh and high. Market volatility is split into three categories of low, normal and high. Additionally, the number of observations and mean values of stock liquidity and market volatility are analyzed under both liquidity demand and market volatility conditions to ensure that the volatility of an observation does not affect the demand for liquidity or vice versa (see appendix 1 and 2).

Table 7 represents the trade order execution performance under four different liquidity conditions. Slippage, shown in panel A, is used to describe the order execution performance. It is the difference between average price achieved and the price of a security at the time the trade decision is made. The price at the decision time is a benchmark price and the difference between the benchmark price and average price achieved indicates how well the trade order has been executed. The results are shown in basis points (bps) and all trades are normalized as buy orders in order to get comparable results. Negative value in slippage indicates an implementation shortfall, where average price achieved is worse than the benchmark price and positive value in slippage indicates a price improvement, where price achieved is more favorable than the benchmark price. The term slippage refers to the negative value; price improvement term is used when discussing positive values in slippage. The results are shown as a whole and as a buy and sell orders separately to see whether there is any indication on whether the side of an order has any effect on trade performance directly or whether there are significant differences in performances of buy and sell orders under certain market conditions. T-tests are run to see the statistical significance of test results. T-tests are run in pairs in order to test for the significance of differences in slippages under different liquidity conditions and are shown in panel B of Table 7. The total number of observations for all trades is 4508 from which buy orders account for 2015 and sell orders for 2493 orders.

As can be seen on Table 7, there is evidence of statistically significant differences in slippages between the four liquidity conditions. Slippage systematically increases the more liquidity is being consumed, more so in sell orders than buy orders. Rather surprisingly, almost all differences are statistically significant at 1% level of significance, only exception being the mediumhigh-high liquidity demand conditions where the sell orders and all orders on aggregate yield significant results at 5% level of significance and buy orders do not yield significant results at all. Interestingly the only pair with non-significant results, mediumhigh-high, has the widest gaps in their respective demand from liquidity-ratio (see Appendix 2). This is due to the fact that the liquidity condition *high* includes all trades with demand from daily liquidity of 2% and above. Nevertheless, the results are conclusive. The differences in slippage are large and statistically significant when compared under different liquidity demand conditions. Taking all orders into account, the difference in slippage between orders with lowest liquidity demand and orders with highest liquidity demand is as much as 15.321 basis points (bps) on average. The difference is even higher in sell orders, where the difference is 17.790 bps, meaning that, on average, sell orders under high liquidity demand conditions face 0.18% more adverse price movement than sell orders under low liquidity demand conditions.

Table 7. Slippage (Implementation shortfall, IS) of orders categorized by demand for liquidity.
This table presents the price improvement or shortfall between the moments when the order is received and when the order is filled. The European best bid and offer (EBBO) price is used as a definition of stock price at the moment the trade is received. The price at the time the order is filled is the value weighted average price of the order. All orders are normalized as buy orders, i.e. negative slippage indicates adverse price movement, implementation shortfall. Order's volume from the Average Daily Volume (denoted %ADV) is used to describe liquidity demand of an order, and is used to split observations equally into four categories: Low, moderate, mediumhigh and high. Low liquidity demand contains orders with %ADV from 0% to 0.44%, moderate contains orders with %ADV between 0.45% and 0.93%, mediumhigh contains orders with %ADV from 0.94% to 1.99% and high contains all orders that have %ADV at or above 2%. The orders are all in OMXH25 stocks filled by using trading algorithms, excluding special algorithms that are designed for special purposes such as after-hours trading. Orders are filled in both lit markets and dark pools. T-tests are run on the slippages in pairs, i.e. 'low-moderate' tests the statistical difference of means with liquidity consumption of low and moderate. The symbols **, ** and * denote the significance at 1%, 5% and 10%, respectively.

A	Demand for liquidity				
	Low	Moderate	Mediumhigh	High	Average value
All trade orders					
Slippage	-8.468	-12.5	-20.005	-23.789	-16.183
Observ.	1131	1126	1123	1128	4508
Buy orders					
Slippage	-8.219	-12.265	-18.223	-20.707	-15.06
Observ.	439	549	508	519	2015
Sell orders					
Slippage	-8.626	-12.724	-21.476	-26.416	-17.09
Observ.	692	577	615	609	2493

B	Low-Moderate	Low-Mediumhigh	Low-High	Moderate-Mediumhigh	Moderate-High	Mediumhigh-High
All trade orders						
Difference	4.032	11.537	15.321	7.505	11.289	3.784
P-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0242
Significance	***	***	***	***	***	**
Buy orders						
Difference	4.046	10.004	12.488	5.958	8.442	2.484
P-value	0.0087	0.0000	0.0000	0.0016	0.0001	0.2851
Significance	***	***	***	***	***	
Sell orders						
Difference	4.098	12.850	17.79	8.752	13.692	4.940
P-value	0.0001	0.0000	0.0000	0.0000	0.0000	0.0387
Significance	***	***	***	***	***	**

In Table 8 the slippage is examined under three different market volatility conditions: low, normal and high. Similarly to Table 7, the orders are analyzed as a whole and then as a buy and sell orders separately. All trades are normalized as buy orders and t-tests are run to see whether the differences are statistically significant.

Unlike liquidity, volatility does not appear to have meaningful impact on trade execution performance in terms of slippage. The differences in slippages under different volatility regimes are negligible and not statistically significant. Only the differences in slippage between low and high market volatility environments provide statistically significant results in sell orders and orders in total, indicating that the side of an order may have an effect when executing orders at low or high market volatility conditions. Later in this thesis, the differences in buy and sell orders are examined more thoroughly with the presentation of probable reasons for why the results are significant in sell orders but not in buy orders. Compared to slippages under liquidity demand conditions in Table 7, where the differences in means are large and statistically significant, the differences in means under market volatility conditions are small and not statistically significant.

Table 8. Slippage (Implementation shortfall, IS) of orders under different market volatility conditions. This table presents the price improvement or shortfall between the moments when the order is received and when the order is filled. The European best bid and offer (EBBO) price is used as a definition of stock price at the moment the trade is received. The price at the time the order is filled is the value weighted average price of the order. All orders are normalized as buy orders, i.e. negative slippage indicates adverse price movement. Euro Stoxx 50 Volatility index (V2X) is used as a proxy for market volatility. Market volatility levels are gained by gathering the market volatility index points from the time periods of this study and dividing it into three equally large categories. Low market volatility contains V2X index points from 12.713 to 18.5097, normal volatility contains index points from 18.5935 to 22.5806 and high market volatility includes index points ranging from 22.7637 to 40.803. The orders are all in OMXH25 stocks filled by using trading algorithms, excluding special algorithms that are designed for special purposes such as after-hours trading. Orders are filled in both lit markets and dark pools. In panel B, t-tests are run in pairs in order to test the significance of differences in slippages between different market volatility conditions. The symbols **, ** and * denote the significance at 1%, 5% and 10%, respectively

	Market volatility			
A	Low	Normal	High	Averaged value
All trade orders				
Slippage	-15,016	-16,456	-17,078	-16,183
Observ.	1504	1503	1501	4508
Buy orders				
Slippage	-14,363	-16,067	-14,767	-15,06
Observ.	650	656	709	2015
Sell orders				
Slippage	-15,513	-16,757	-19,147	-17,09
Observ.	854	847	792	2493

B	Low-Normal	Low-High	Normal-High
All trade orders			
Difference	1.440	2.062	0.622
P-value	0.2008	0.0709	0.6254
Significance		*	
Buy orders			
Difference	1.704	0.404	-1.300
P-value	0.3447	0.7950	0.4805
Significance			
Sell orders			
Difference	1.244	3.634	2.390
P-value	0.3843	0.0269	0.1751
Significance		**	

Test results indicate that order execution performance in terms of slippage varies significantly under different stock liquidity conditions and high liquidity demand results in higher trading costs, increasing slippage and hampering trade execution performance. The results also indicate that, while liquidity appears to clearly affect slippage, volatility does not have statistically significant effect on execution performance. Next, Kendall's Tau nonparametric test is used to analyze whether liquidity demand and volatility correlate with slippage. Kendall's Tau rank correlation coefficient is used to measure the ordinal association between slippage and liquidity demand and between slippage and market volatility.

Table 9 presents the results of Kendall's Tau measures of association between slippage, liquidity demand and volatility, respectively. Relatively same amount of concordances and discordances would indicate that there is no positive nor negative association between two variables. If concordances (C) have significantly bigger score than discordances (D), we shall say that the pair is concordant, i.e. there is a positive association between given variables. Naturally, if discordances (D) have significantly bigger score than concordances (C), there appears to be negative relationship between given variables. Score (S) is simply the difference between concordances (C) and discordances (D). Tau-b and tau-a correlation coefficients describe the strength and side of the relationship between variables. A total of 4508 parent orders were analysed in conducting the Kendall's Tau association analysis.

Table 9. Kendall's Tau non-parametric statistical association between slippage, liquidity demand and market volatility.
This table shows the results from Kendall's Tau non-parametric test. In the test, values are rearranged in ordinal fashion and the resulting ranking orders are compared between variables to see whether the ranking orders correlate with each other between two variables. In this instance, slippage is being analyzed with liquidity demand and market volatility. Tau-a and tau-b describe the strength of the correlation, score is the difference of concordances minus discordances and probability shows the statistical significance of the test. A total of 4508 parent orders are being analyzed.

	All orders		**Buy orders**		**Sell orders**	
	Demand for liquidity	Market volatility	Demand for liquidity	Market volatility	Demand for liquidity	Market volatility
tau-b	-0.106003	-0.004431	-0.084911	0.009110	-0.126392	-0.016174
tau-a	-0.105791	-0.004421	-0.084733	0.009088	-0.126117	-0.016133
Score (S)	-1074708	-44913	-171933	18441	-391756	-50114
Concordances (C)	4521779	5034041	924349	1018986	1350534	1520292
Discordances (D)	5596487	5078954	1096282	1000545	1742290	1570406
Probability	0.0000	0.6563	0.0000	0.5409	0.0000	0.2273
Observations	4508	4508	2015	2015	2493	2493

As can be seen from Table 9, there are more discordances than concordances when testing for the association between slippage and liquidity demand. This indicates a negative association between these two variables, which can also be seen from the negative tau-b and tau-a values. The results indicate that slippage, which is an adverse price movement during the duration of an order, have correlation with liquidity demand. The negative association between these two variables is statistically significant and fairly strong, especially when taking into account the noise and other factors driving the share prices. Testing for statistical associations in sell and buy orders separately yield similar results. The association between slippage and liquidity demand is statistically significant and while the association is fairly strong in both buys and sells, it is more so in sell orders. These results are in line with the earlier results from t-tests suggesting statistically significant differences in means of slippages, especially in sell orders.

On the other hand, no evidence of statistically significant association between slippage and market volatility is found. There are barely any differences in concordances and discordances, resulting in tau-a and tau-b statistics close to zero. The results indicate that market volatility does not have an effect on slippage. Testing for statistical associations between slippage and market volatility in buy and sell orders separately yield similar results, further confirming the lack of correlation between slippage and market volatility.

5.2 Price reversion

In this chapter trade execution performance is analyzed in terms of price reversion. This is done by analyzing post-trade price movement in intervals of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes after executing an order. All orders are normalized as buy orders so that a negative price reversion implies an adverse price movement, i.e. the share price deteriorates (improves) after a buy (sell) order is finished. In their analysis of price reversion, Almgren et al. (2012) conclude most of the temporary price impact dissipates 30 minutes after the completion of an order. Based on their findings, I make an assumption that the 30 and 60 minute time point intervals represent the permanent price movement of an order while the time intervals up to 15 minutes are assumed to represent the temporary price movement. The average price changes are obtained by using an arithmetic mean. T-tests are then run in pairs in similar fashion than in analyzing slippage.

Table 10 and Figure 4 present the test results in price reversion on six time intervals mentioned earlier. On average, the post-trade price movement is negative in all cases, indicating a presence of systematic adverse price movement following an order fill. The differences in means are statistically significant when the liquidity demand rank differs by at least two ranks. For example, the results are statistically significant between pairs of low and medium-high, low and high, and moderate and high to some extent. On the other hand, no evidence of significant differences in price reversion is found when analyzing liquidity demand ranks that are close to each other. Before drawing conclusions from these results, it is important to keep in mind that the analysis was done in the 25 largest stocks in Finnish stock exchange, which are often also the most traded ones. Especially in 30 minute and 60 minute time intervals a number of factors can affect the movement in share price. Nevertheless, all things considered the price reversion is systematically higher when the liquidity demand is high in comparison to order fills with low liquidity demand. In addition, the results suggest that a small change in liquidity demand do not necessarily result in different price reversions. The difference in liquidity demand has to be at least two ranks before any notable differences in temporary or permanent price impacts are found.

Table 10. Stock price movement of all trade orders under liquidity conditions over time intervals after last fill.

This table presents average price movement in stock price (bps) over time intervals under four liquidity demand levels: low, moderate, mediumhigh and high. The breakdown of liquidity demand levels in this study is the same than described in table 7. The movement in stock price is measured relative to the stock price at the time of a last fill. The last fills are normalized as buy order fills so that a positive reversion denotes price improvement and a negative reversion denotes price deterioration. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Liquidity demand	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	Observ.
Low	-3.904	-4.68	-5.52	-5.604	-4.3	-3.719	1131
Moderate	-4.96	-7.118	-7.804	-7.875	-9.043	-9.157	1126
Mediumhigh	-5.416	-7.965	-9.748	-10.958	-11.893	-14.407	1123
High	-5.119	-8.162	-10.445	-12.209	-15.896	-21.028	1128
Average	-4.849	-6.979	-8.376	-9.158	-10.278	-12.071	4508

B

	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Moderate						
Difference	1.056	2.438	2.284	2.271	4.743	5.438
P-value	0.0340	0.0238	0.1193	0.2159	0.0750	0.1144
Significance	**	**			*	
Low-Mediumhigh						
Difference	1.512	3.285	4.228	5.354	7.593	10.688
P-value	0.0039	0.0081	0.0043	0.0018	0.0008	0.0007
Significance	***	***	***	***	***	***
Low-High						
Difference	1.215	3.482	4.925	6.605	11.596	17.309
P-value	0.0261	0.0006	0.0002	0.0000	0.0000	0.0000
Significance	**	***	***	***	***	***
Moderate-Mediumhigh						
Difference	0.456	0.847	1.944	3.083	2.850	5.250
P-value	0.3637	0.4748	0.1843	0.0835	0.2701	0.0989
Significance				*		*
Moderate-High						
Difference	0.159	1.044	2.641	4.334	6.853	11.871
P-value	0.7621	0.2665	0.0436	0.0104	0.0054	0.0001
Significance			**	**	***	***
Mediumhigh-High						
Difference	-0.297	0.197	0.697	1.251	4.003	6.621
P-value	0.5892	0.8610	0.5982	0.4202	0.0461	0.0115
Significance					**	**

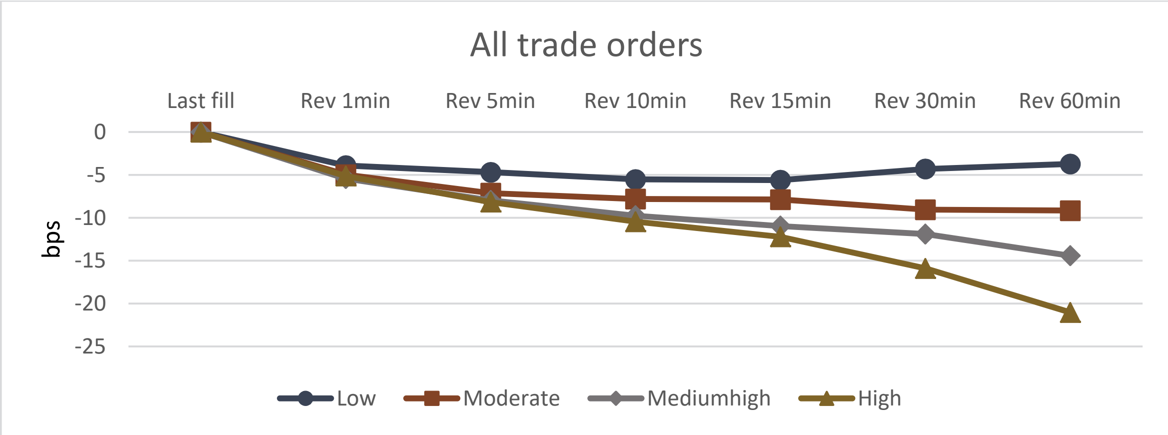


Figure 4. Stock price movement of all trades under different liquidity conditions after the last fill. The price of the last fill is normalized as zero and the points at the time intervals represent price reversions in relation to the last fill. All trade orders are normalized as buy orders.

Tables 11 and 12 present the test results in price reversion under four liquidity demand conditions for buy and sell orders, respectively. Figure 5 represents the results in a graphical form. In buy orders, the tests results do not yield as clear evidence compared to results from analyzing all orders as a whole. As can be seen in Table 11, the average price reversions do not systemically increase with the increases in liquidity demand. None of the price reversion differences in 1, 5, 10 and 15 minute time intervals are statistically significant. On average, the price reversion in 1 minute time interval is higher in low liquidity demand trades than in high liquidity demand trades. In contrast to findings on Table 10, the results in buy orders are rather surprising. Sell orders on the other hand provide results that are in line with the results seen on Table 10 as can be seen on Table 12. Again, the differences in price reversions are statistically significant when the difference between liquidity demands is two ranks or more. In addition, the range between smallest and highest average price reversions is slightly wider in sell orders than in buy orders. In the light of evidence presented in Tables 11 and 12, it does appear that liquidity demand has a bigger impact on price reversion in sell orders than buy orders.

Table 11. Stock price movement after buy order fills under four liquidity conditions over time intervals.

This table presents average price movement in stock price (bps) of buy orders over time intervals under four liquidity demand levels: low, moderate, mediumhigh and high. The breakdown of liquidity demand levels in this study is the same than described in table 7. The movement in stock price is measured relative to the stock price at the time of a last fill. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Liquidity demand	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	*Observ.*
Low	-4,589	-6,395	-6,994	-7,297	-6,068	-8,446	439
Moderate	-4,616	-6,835	-7,332	-8,064	-8,688	-10,516	549
Mediumhigh	-4,376	-6,935	-7,885	-9,386	-9,39	-11,119	508
High	-4,313	-7,904	-10,261	-11,521	-14,331	-20,843	519
Average	-4,471	-7,04	-8,152	-9,121	-9,748	-12,877	2015

B

	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Moderate						
Difference	0.027	0.44	0.338	0.767	2.62	2.07
P-value	0.9696	0.7543	0.8752	0.7527	0.4511	0.6853
Significance						
Low-Mediumhigh						
Difference	-0.213	0.54	0.891	2.089	3.322	2.673
P-value	0.7646	0.7187	0.6717	0.4089	0.3374	0.5922
Significance						
Low-High						
Difference	-0.276	1.509	3.267	4.224	8.263	12.397
P-value	0.7175	0.2804	0.1122	0.1008	0.0113	0.0068
Significance					**	***
Moderate-Mediumhigh						
Difference	-0.240	0.100	0.553	1.322	0.702	0.603
P-value	0.7271	0.9417	0.7793	0.5295	0.8133	0.8904
Significance						
Moderate-High						
Difference	-0.303	1.069	2.929	3.457	5.643	10.327
P-value	0.6779	0.4039	0.1295	0.1077	0.0428	0.0099
Significance					**	***
Mediumhigh-High						
Difference	-0.063	0.969	2.376	2.135	4.941	9.724
P-value	0.9319	0.4786	0.2060	0.3387	0.0707	0.0107
Significance					*	**

Figure 5. Stock price movement of buy and sell orders under different liquidity conditions after the last fill.
The price of the last fill is normalized as zero and the points at the time intervals represent price reversions in relation to the last fill. The sell orders are not normalized as buy orders in this figure.

Analyzing price reversion of buy and sell orders separately yields some interesting findings. As can be seen on Table 11, there is barely any evidence of statistically significant differences in price reversion. This holds true even in most extreme differences between low liquidity demand and high liquidity demand conditions. The results from price reversion analysis of sell orders (Table 12) support the findings from Table 10 where the price reversions of all trades were examined. Whereas sell orders appear to be sensitive to liquidity demand in terms of price reversion, buy orders appear to be insensitive to it. In addition, no evidence of significant differences in price reversions between mediumhigh and high liquidity demand conditions is found, neither in buy orders nor sell orders. This is rather counter-intuitive as the average trade order volume to average daily volume ratio is 4.26% on sell orders under high liquidity demand conditions, almost three times the ratio under mediumhigh liquidity demand conditions (1.44%). Also, market participation rate averages 119.88% under high liquidity demand conditions compared to medium-high's average of 58.44% while the percentage of how much is executed on primary venue (OMXH Helsinki) is almost equal. Comparing the differences in means of liquidity demands between the four bins within one rank from each other, the differences are largest between mediumhigh and high liquidity demand conditions (Appendix 2). The analysis of slippage showed similar findings in that the evidence of significant differences between mediumhigh and high liquidity demand conditions was not as strong as in other pairs.

Another finding worth noting is the price reversion at 60 minute time interval under low liquidity demand conditions. In sell orders, the reversion is less than one basis point, indicating an absence of permanent price impact. However, this is not the case in buy orders where the reversion at 60 minute time interval is 8.446 bps. Adding to the fact the mainly non-significant differences in price reversion after buy order fills makes the totally different behavior in price movement after buy order fills even more puzzling and warrants a further analysis on a micro level.

Table 12. Stock price movement after sell order fills under four liquidity conditions over time intervals.

This table presents average price movement in stock price (bps) of sell orders over time intervals under four liquidity demand levels: low, moderate, mediumhigh and high. The breakdown of liquidity demand levels in this study is the same than described in table 7. The movement in stock price is measured relative to the stock price at the time of a last fill. The last fills are normalized as buy order fills so that a positive reversion is price improvement and a negative reversion is price deterioration. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Liquidity demand	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	*Observ.*
Low	-3.47	-3.592	-4.585	-4.529	-3.179	-0.72	692
Moderate	-5.288	-7.387	-8.253	-7.694	-9.381	-7.863	577
Mediumhigh	-6.275	-8.816	-11.286	-12.256	-13.961	-17.123	615
High	-5.806	-8.381	-10.602	-12.796	-17.23	-21.185	609
Average	-5.153	-6.929	-8.557	-9.187	-10.707	-11.419	2493

B	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Moderate						
Difference	1.818	3.795	3.668	3.165	6.202	7.143
P-value	0.0089	0.0168	0.0688	0.2373	0.1135	0.1285
Significance	***	**	*			
Low-Mediumhigh						
Difference	2.805	5.224	6.701	7.727	10.782	16.403
P-value	0.0002	0.0047	0.0011	0.0009	0.0003	0.0001
Significance	***	***	***	***	***	***
Low-High						
Difference	2.336	4.789	6.017	8.267	14.051	20.465
P-value	0.0023	0.0008	0.0006	0.0001	0.0000	0.0000
Significance	***	***	***	***	***	***
Moderate-Mediumhigh						
Difference	0.987	1.429	3.033	4.562	4.58	9.26
P-value	0.1716	0.4474	0.1564	0.1033	0.2648	0.0436
Significance						**
Moderate-High						
Difference	0.518	0.994	2.349	5.102	7.849	13.322
P-value	0.4895	0.4663	0.1872	0.0473	0.0469	0.0024
Significance				**	**	***
Mediumhigh-High						
Difference	-0.469	-0.435	-0.684	0.540	3.269	4.062
P-value	0.5578	0.7999	0.7117	0.8024	0.2579	0.2595
Significance						

Next the price reversion is analyzed under different market volatilities. Market volatility is split into three categories of low, normal and high market volatility. The observations are categorized into these market volatilities similarly than in slippage analysis. The time intervals used for price reversion are similar to the ones used earlier.

Table 13 and Figure 6 below show the post-trade stock price movement under different market volatility conditions. As seen on Table 13, there is no evidence of statistically significant differences in price reversions under different market volatility conditions. In fact, even the means provide mixed results in that the price reversion could be higher under times of low volatility than in times of high volatility. Out of 18 tests, only three provide statistically significant results, of which two are statistically significant at the 5% significance level and one is statistically significant at 10% significance level. One of these tests that provide statistically significant difference is the difference between low and normal market volatility conditions 30 minutes after the order fill. However, the result is unexpected in that the price reversion appears to be significantly greater under low market volatility than in normal market volatility environment. It would appear that market volatility has no effect on neither slippage nor price reversion. Considering the fact that high market volatility implies high uncertainty and large variations in prices, it is surprising to see larger price reversion in times of low market volatility compared to high market volatility. One of the reasons could be that the signal generated by a trade order is easier to discern in times of low volatility.

Table 13. Stock price movement under different market volatility conditions over time intervals after last fill.

This table presents average price movement in stock price (bps) over time intervals under three market volatility conditions: low, normal and high. Euro stoxx 50 volatility index (V2X) is used as a proxy for market volatility. The movement in stock price is measured relative to the stock price at the time of a last fill. The last fills are normalized as buy order fills so that a positive reversion is price improvement and a negative reversion is price deterioration. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Volatility	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	*Observ.*
Low	-4,632	-6,955	-8,924	-9,51	-12,02	-13,666	1504
Normal	-4,707	-6,445	-6,664	-7,683	-7,979	-11,417	1503
High	-5,207	-7,536	-9,541	-10,281	-10,835	-11,126	1501
Average	-4,849	-6,979	-8,376	-9,158	-10,278	-12,071	4508

B	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Normal						
Difference	0.075	-0.51	-2.26	-1.827	-4.041	-2.249
P-value	0.8743	0.6101	0.0655	0.2126	0.0436	0.3785
Significance			*		**	
Low-High						
Difference	0.575	0.581	0.617	0.771	-1.185	-2.54
P-value	0.1661	0.5039	0.5870	0.5787	0.5467	0.3149
Significance						
Normal-High						
Difference	0.5	1.091	2.877	2.598	2.856	-0.291
P-value	0.2882	0.2676	0.0229	0.0967	0.1879	0.9197
Significance			**			

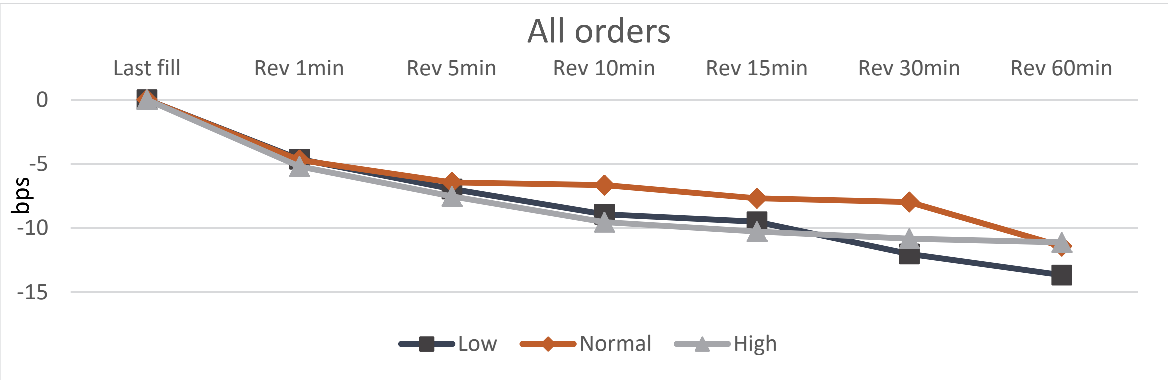


Figure 6. Stock price movement of all trade orders under different volatility conditions after the last fill.

The price of the last fill is normalized as zero and the points at the time intervals represent price reversions in relation to the last fill.

Tables 14 and 15 below show the results in price reversion after buy and sell orders, respectively. Figure 7 presents the results in a graphical form. There is no evidence of statistically significant differences in price reversions after buy orders, but significant differences are found after sell orders. Price reversion is the most favorable in times of normal market volatility. As can be seen on Table 15, sell orders in times of high market volatility lead to higher adverse price movement after an order fill. This could be caused by the simple market reaction in uncertain times when volatility increases as investors tend to sell their positions due to uncertainty. This will be discussed in more detail in next chapter.

Table 14. Stock price movement of buy orders under different market volatility conditions over time intervals after last fill.
This table presents average price movement in stock price (bps) of buy orders over time intervals under three market volatility conditions: low, normal and high. Euro stoxx 50 volatility index (V2X) is used as a proxy for market volatility. The breakdown of market volatility levels in this study is exactly the same than in other statistical tests in this study. The movement in stock price is measured relative to the stock price at the time of a last fill. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Volatility	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	*Observ.*
Low	-4,834	-7,218	-9,381	-10,487	-13,393	-14,303	650
Normal	-4,635	-7,765	-7,597	-9,222	-9,266	-11,94	656
High	-3,988	-6,206	-7,538	-7,775	-6,852	-12,436	709
Average	-4,471	-7,04	-8,152	-9,121	-9,748	-12,877	2015

B	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Normal						
Difference	-0.199	0.547	-1.784	-1.265	-4.127	-2.363
P-value	0.7627	0.6512	0.3208	0.5304	0.1171	0.5304
Significance						
Low-High						
Difference	-0.846	-1.012	-1.843	-2.712	-6.541	-1.867
P-value	0.1658	0.3746	0.2600	0.1607	0.0122	0.6210
Significance					**	
Normal-High						
Difference	-0.647	-1.559	-0.059	-1.447	-2.414	0.496
P-value	0.2886	0.2077	0.9735	0.4883	0.3905	0.9029
Significance						

Table 15. Stock price movement of sell orders under different market volatility conditions over time intervals after last fill.

This table presents average price movement in stock price (bps) of sell orders over time intervals under three market volatility conditions: low, normal and high. Euro stoxx 50 volatility index (V2X) is used as a proxy for market volatility. The breakdown of market volatility levels in this study is exactly the same than in other statistical tests in this study. The movement in stock price is measured relative to the stock price at the time of a last fill. The last fills are normalized as buy order fills so that a positive reversion is price improvement and a negative reversion is price deterioration. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burqundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. T-tests are run in pairs on the price change observations to test whether the average movements in price over time intervals are different from each other. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

A

Volatility	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min	*Observ.*
Low	-4.479	-6.755	-8.576	-8.766	-10.974	-13.181	854
Normal	-4.763	-5.422	-5.94	-6.491	-6.983	-11.012	847
High	-6.299	-8.728	-11.335	-12.524	-14.4	-9.954	792
Average	-5.153	-6.929	-8.557	-9.187	-10.707	-11.419	2493

B	Rev 1min	Rev 5min	Rev 10min	Rev 15min	Rev 30min	Rev 60min
Low-Normal						
Difference	0.284	-1.333	-2.636	-2.275	-3.991	-2.169
P-value	0.6716	0.3762	0.1157	0.2736	0.1695	0.5318
Significance						
Low-High						
Difference	1.82	1.973	2.759	3.758	3.426	-3.227
P-value	0.0013	0.1234	0.0800	0.0565	0.2328	0.3437
Significance	***		*	*		
Normal-High						
Difference	1.536	3.306	5.395	6.033	7.417	-1.058
P-value	0.0276	0.0258	0.0024	0.0082	0.0210	0.7948
Significance	**	**	***	***	**	

Figure 7. Stock price movement of buy and sell orders under different volatility conditions after the last fill.
The price of the last fill is normalized as zero and the points at the time intervals represent price reversions in relation to the last fill. The sell orders are not normalized as buy orders in this figure.

5.3 Differences in buy and sell orders

In this final part of the empirical test results chapter, buy and sell orders are analyzed in more detail. Where in earlier parts of this chapter, the significance of differences between different market conditions was tested, now the focus is in the differences between buy and sell orders under certain market conditions. First, the slippage and price reversion is analyzed under liquidity conditions discussed above. The aim is to find statistically significant differences in means and to find probable reasons for the possible differences. Lastly, the slippage and price reversion under the three market volatility conditions are analyzed.

Not many statistically significant results can be found from Table 16. While the liquidity demand, in the light of previous studies and results found on this thesis, is a big driver in execution performance, it appears that it does not matter which side a trader takes when executing an order. However, few interesting details can be found on Table 16. When demand for liquidity is high (more than 2% of average daily volume), sell orders tend to be significantly more costly than buy orders in terms of slippage. The difference in slippage is almost six basis points which is almost double in contrast to the difference between buy and sell orders under medium-high liquidity demand condition. Another interesting finding is the one-minute price reversion. Under medium-high and high liquidity demand conditions, difference in price reversion between buy and sell orders is statistically significant. In both cases, sell orders face more price reversion than buy orders. After one minute, the differences in price reversions dissipate and there is no further evidence on whether side matters when executing an order with high or low demand for liquidity.

Table 16. Slippage and stock price movement of buy and sell orders under liquidity conditions.
This table presents the slippage and price reversions under four liquidity conditions. Slippage is the difference in basis points between the price at the moment a trade order is received and when it is completely filled. The price reversion is measured relative to the stock price at the time of a last fill. All orders are normalized as buy orders, i.e. in buy (sell) orders negative slippage indicates price appreciation (depreciation) during the order fill and negative price reversion implies price depreciation (appreciation) in stock price after the order is filled. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. The difference is calculated by taking the difference between the averages of buy and sell orders. A positive difference indicates sell order faces more slippage or price reversion and vice versa for negative difference values. T-tests are run between buy and sell orders to see whether there is evidence that one side performs systemically better than the other in certain situations. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

		Demand for liquidity			
		Low	Moderate	Mediumhigh	High
Implementation shortfall					
	Buy	-8.219	-12.265	-18.223	-20.707
	Sell	-8.626	-12.724	-21.476	-26.416
	Difference	0.407	0.459	3.254	5.708
	P-value	0.675	0.762	0.119	0.031**
Reversion 1M					
	Buy	-4.589	-4.616	-4.376	-4.313
	Sell	-3.47	-5.288	-6.275	-5.806
	Difference	-1.118	0.671	1.9	1.493
	P-value	0.138	0.317	0.011**	0.065*
Reversion 5M					
	Buy	-6.395	-6.835	-6.935	-7.904
	Sell	-3.592	-7.387	-8.816	-8.381
	Difference	-2.803	0.552	1.881	0.477
	P-value	0.089*	0.701	0.322	0.695
Reversion 10M					
	Buy	-6.994	-7.332	-7.885	-10.261
	Sell	-4.585	-8.253	-11.286	-10.602
	Difference	-2.409	0.921	3.402	0.341
	P-value	0.263	0.653	0.105	0.835
Reversion 15M					
	Buy	-7.297	-8.064	-9.386	-11.521
	Sell	-4.529	-7.694	-12.256	-12.796
	Difference	-2.768	-0.37	2.87	1.275
	P-value	0.28	0.891	0.221	0.536
Reversion 30M					
	Buy	-6.068	-8.688	-9.39	-14.331
	Sell	-3.179	-9.381	-13.961	-17.23
	Difference	-2.89	0.692	4.571	2.9
	P-value	0.396	0.868	0.136	0.268
Reversion 60M					
	Buy	-8.446	-10.516	-11.119	-20.843
	Sell	-0.72	-7.863	-17.123	-21.185
	Difference	-7.726	-2.652	6.004	0.342
	P-value	0.118	0.591	0.138	0.919

Table 17 presents the differences between buy and sell orders under different market volatility conditions. The results are quite different compared to earlier findings regarding slippage and price reversion under different volatility conditions. As can be seen in the Table 17 below, the differences that are statistically significant are all in times of high volatility. In fact, all but the 60-minute price reversion provide statistically significant results. In all of these cases the sell order faces higher slippage and price reversion, and the gap between buy and sell order price reversions grows wider the more time passes after the last fill. The evidence is clear that buy orders perform better than sell orders under high market volatility. High market volatility typically indicates a market distress or uncertainty, and the prices tend to go down as a result as investors want to get rid of their stocks. Based on this fact, the reason behind these results is quite simple: When the volatility is high, sell orders perform worse as the trader has to run with all other investors, trying to find a buyer for his stocks. After the order is filled, the amplified downward movement in price results in an opportunity for other investors to buy at a discount and the price movement turns momentarily so that the stock price starts to go up instead as a result of market impact. The evidence of that happening is found in Table 17 where the price reversion in sell orders increases over time. Between 30-minute and 60-minute time intervals we see the temporary effect dissipate as the price reversion in sell orders starts to go down, indicating that stock price is going down again.

Buy order slippage and price reversions tell a different story. As the markets tend to go down in times of high volatility, being on buying side is beneficial to the trader. The other market participants, most of which are sellers in times of high volatility, could be more prone to cross the spread to hit the buyer's bid prices. After the buy order is finished, the market movement continues its downward movement as can be seen from the increasing price reversions as the time passes. In conclusion, in times of high volatility a sell order has to run with other investors and is followed by a temporary upward price movement that dissipates after around 30 minutes. If the trader is on the buying side, the market movement goes through the buy order without a noticeable price impact caused by the buy order. However, a negative slippage in buy orders implies that the price goes up when the order is being executed. This indicates that the sellers do not exclusively cross the spread to hit the liquidity provided by a buy order and there are other market participants running along and trading ahead, taking the advantage of a buy order and driving the price up for the duration of an order.

Table 17. Slippage and stock price reversion of buy and sell orders under different market volatility conditions.
This table presents the slippage and price reversions under three market volatility conditions. Slippage is the difference in basis points between the average trade price and the price at the moment a trade order is received. The price reversion is measured relative to the stock price at the time of a last fill. All orders are normalized as buy orders, i.e. in buy (sell) orders negative slippage indicates price appreciation (depreciation) during the order fill and negative price reversion implies price depreciation (appreciation) in stock price after the order is filled. The European best bid and offer (EBBO) mid-price is used as a definition of stock price. The EBBO mid-price is defined as the mid-point of the highest bid price and lowest offer price that are available in the Helsinki Stock Exchange, Chi-X Europe, BATS Europe, Burgundy, and Turquoise. The movement in price in bps over a time interval is calculated as the difference between the EBBO mid-price at the time after a fill and the execution-time EBBO mid-price, divided by the execution-time EBBO mid-price. The table shows the average movement in EBBO mid-price for times after fill of 1 minute, 5 minutes, 10 minutes, 15 minutes, 30 minutes and 60 minutes. Average price changes are obtained by using an arithmetic mean. The difference is calculated by taking the difference between the averages of buy and sell orders. A positive difference indicates sell order faces more slippage or price reversion and vice versa for negative difference values. T-tests are run between buy and sell orders to see whether there is evidence that one side performs systemically better than the other in certain situations. The symbols ***, ** and * denote the significance at the 1%, 5% and 10% level, respectively.

		Market volatility	
	Low	Normal	High
Implementation shortfall			
Buy	-14.363	-16.067	-14.767
Sell	-15.513	-16.757	-19.147
Difference	1.15	0.69	4.38
P-value	0.407	0.701	0.016**
Reversion 1M			
Buy	-4.834	-4.635	-3.988
Sell	-4.479	-4.763	-6.299
Difference	-0.355	0.128	2.311
P-value	0.554	0.864	0.0001***
Reversion 5M			
Buy	-7.218	-7.765	-6.206
Sell	-6.755	-5.422	-8.728
Difference	-0.462	-2.343	2.522
P-value	0.716	0.136	0.036**
Reversion 10M			
Buy	-9.381	-7.597	-7.538
Sell	-8.576	-5.94	-11.335
Difference	-0.806	-1.657	3.797
P-value	0.606	0.388	0.023**
Reversion 15M			
Buy	-10.487	-9.222	-7.775
Sell	-8.766	-6.491	-12.524
Difference	-1.721	-2.731	4.749
P-value	0.346	0.241	0.025**
Reversion 30M			
Buy	-13.393	-9.266	-6.852
Sell	-10.974	-6.983	-14.4
Difference	-2.419	-2.283	7.549
P-value	0.341	0.467	0.013**
Reversion 60M			
Buy	-14.303	-11.94	-12.436
Sell	-13.181	-11.012	-9.954
Difference	-1.122	-0.928	-2.481
P-value	0.714	0.823	0.54

5.4 Discussion

The aim of the empirical tests was to answer the question whether overall market conditions have a significant impact to performance of trading algorithms. The first research question is *Do the market conditions have an effect on implementation shortfall?* In the light of empirical evidence provided in this thesis, I provide conclusive evidence that the execution performance is greatly associated with the liquidity of the stock. Therefore the null hypothesis *There is no evidence of association between stock liquidity and IS* can be rejected. However, the empirical tests did not find any evidence of association between market volatility and implementation shortfall, therefore the second null hypothesis *There is no evidence of association between market volatility and IS* cannot be rejected. After further analyzing whether the side of the trade (buy or sell) affects the implementation shortfall, the test results suggest that in terms of implementation shortfall (slippage), the side of the trade does not matter in any stock liquidity condition, but when the overall market volatility is high, sell trade order execution is significantly poorer than the execution of buy orders.

The second research question refers to the price reversion following after the last fill of a parent order and goes as follows: *Do the market conditions have an effect on price reversion?* The analysis is done on all trade orders on aggregate, and on buy and sell orders, respectively. As the results indicate the side of the trade does matter in terms of price reversion, answering the second research question is not as straightforward as the first one. The third null hypothesis is *There is no evidence of differences in means of price reversion values under different stock liquidity conditions.* After analyzing price reversion on all trades on aggregate, there is evidence of differences in mean values when the stock liquidity condition differs by at least two ranks. In other words, the stock liquidity does affect the price reversion, but only when there is a significant difference in demand for liquidity. Testing for sell orders only provide similar results, indicating that the null hypothesis can be rejected. However, testing for buy orders only provide no evidence of differences in means of price reversion values. Therefore, the null hypothesis cannot be conclusively rejected. In addition, there is no indication that the side of the trade matters in terms of price reversion under different stock liquidity conditions. The fourth and last null hypothesis is *There is no evidence of differences in means of price reversion values under* *different market volatility conditions.* No evidence of significant differences in means of price reversion values is found when testing for all trades on aggregate. Testing for buy orders only provide similar results in that no evidence of differences is found. Testing for sell orders only, however, provide statistically significant results between price reversion values under normal and high market volatility conditions, indicating that the price reversion is the most favorable under normal market volatility conditions, and high volatility results in significantly higher price reversion. Test results of whether the side of the trade matters under different market volatility conditions provide evidence of statistically significant differences when the market volatility is high. Price reversion is significantly higher after sell orders than buy orders. This indicates that when the market volatility is high, the algorithm has to compete with other market participants during the selloff, trying to find matching buy orders. After the sell order is completed, the price reverts back to pre-sell levels. The fourth null hypothesis cannot be conclusively rejected as the market volatility has an effect on the price reversion in only sell orders.

This thesis is done on a macro level to give insight of how the parent orders perform under varying market conditions in general. Future research could use the findings of this thesis to conduct more micro level analysis on a fill by fill level in order to find out what happens in the markets when the order is being filled under certain market conditions. In addition, future research in transaction cost analysis with knowledge of which trades have been executed against HFTs would provide more valuable information and answer the question on HFT activity under different market conditions. Lastly, as this thesis is highly focused to the viewpoint of a Finnish Asset Management company, the results cannot be generalized. In order to make more generalizable conclusions, more analysis need to be done from the viewpoint of numerous market participants.

6. Conclusion

In this thesis, I have analyzed trade execution performance in terms of slippage (implementation shortfall, IS) and price reversion. The focus of the analysis was to find possible significant differences in slippages and price reversions under varying stock liquidity and market volatility conditions. The analysis is done on OMXH25 stocks executed at various trading venues by using trading algorithms. The purpose of this analysis was to find out whether there is a systemic pattern in under which market conditions trade execution suffers the most, indicating a possible information leakage or exposure to uncertainty in execution.

Based on the empirical tests conducted in this thesis, a strong association is found between stock liquidity and implementation shortfall. The more liquidity is being consumed by a trade order, the higher the adverse price movement for the duration of an order is. Stock liquidity affects the post-trade price reversion as well, to a smaller extent. While marginal differences in liquidity could result in significantly different implementation shortfalls, the difference in liquidity has to be more significant so that the differences in price reversion are significant. In addition, the stock liquidity affects price reversion of sell orders only, while no evidence of significant differences is found on buy order price reversion values under different liquidity conditions.

No association is found between implementation shortfall and market volatility, indicating that other variables drive the adverse price movement when the parent order is being worked. However, the empirical tests find that the side of a trade does matter when executing a trade under different market volatility conditions. While no association is found between implementation shortfall and market volatility, sell orders face significantly higher implementation shortfall than buy orders when the market volatility is high. Market volatility and price reversion provide similar results in that there is no evidence of significant differences in price reversions under different market volatility conditions, with the exception of sell orders. When the market volatility is high, executing a sell order proves to result in significantly higher trading costs than when executing a buy order, in both implementation shortfall and price reversion.

This study indicates that both stock liquidity and market volatility affect the trading costs in their own, unique ways. This thesis fulfilled its purpose of finding whether these market conditions have an effect on the trading costs and it also successfully differentiated in how the side of a trade affects the costs under certain conditions. A logical next step would be to use the findings of this study as a background to analyze more thoroughly, on a fill by fill level, what happens in markets when an order is being executed under certain liquidity and volatility conditions.

Naturally, a trader cannot pick the market conditions for his trades. Sometimes a trade has to be executed even with prevailing difficult volatility and liquidity conditions. However, this study provides insight on what happens to parent orders, on average, under different liquidity and volatility conditions. This insight can be used as a benchmark for future trade executions and it provides knowledge of what can be expected when executing a trade under certain market conditions. Despite the fact that this study is highly specialized in that it covers for one market participant only, some conclusions can be drawn from it. For one, prevailing market conditions can significantly affect the execution performance of an order and it needs to be addressed properly in trade execution. Additionally, trade execution is becoming increasingly more important and heavy investments are made just to pinch a few basis points from trading costs. With current market infrastructure and its players, a trader without proper analytics tools is at a continuous disadvantage which directly affects the portfolio’s returns.

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Appendices

Appendix 1. Number of parent orders under different market volatility and stock liquidity conditions.

All orders		Market volatility			
		Low	Normal	High	Total
Demand for liquidity	Low	387	356	388	1131
	Moderate	337	368	421	1126
	Mediumhigh	363	390	370	1123
	High	417	389	322	1128
	Total	1504	1503	1501	4508

Buy orders		Market volatility			
		Low	Normal	High	Total
Demand for liquidity	Low	127	142	170	439
	Moderate	154	180	215	549
	Mediumhigh	162	166	180	508
	High	207	168	144	519
	Total	650	656	709	2015

Sell orders		Market volatility			
		Low	Normal	High	Total
Demand for liquidity	Low	260	214	218	692
	Moderate	183	188	206	577
	Mediumhigh	201	224	190	615
	High	210	221	178	609
	Total	854	847	792	2493

Appendix 2. Average liquidity demand and market volatility under different liquidity demand and market volatility conditions.

	Demand for liquidity				Market volatility		
Average demand for liquidity	Low	Moderate	Mediumhigh	High	Low	Normal	High
All orders	0.249	0.682	1.424	4.330	1.739	1.721	1.552
Buy orders	0.254	0.685	1.412	4.414	1.971	1.794	1.462
Sell orders	0.248	0.68	1.435	4.257	1.561	1.665	1.634
Average volatility (V2X)							
All orders	21.488	21.724	21.573	20.724	16.568	20.527	27.047
Buy orders	21.922	21.753	21.609	20.447	16.502	20.632	26.650
Sell orders	21.213	21.696	21.543	20.961	16.618	20.446	27.403