# The Relationship between High Frequency Trading and Stock Market Volatility

*An Analysis of the Nordic Stock Markets*

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**Abstract**

This paper investigates the relationship between high frequency trading (HFT) activity and stock market volatility on the Nordic stock markets. The study utilizes a unique dataset that provides a proxy of the fraction of the total market turnover in which HFT firms were involved in the time period from March 2010 to March 2012. The study finds strong evidence for a positive contemporaneous relationship between stock market volatility and the participation level of HFT firms, both on an aggregate monthly and a daily basis. One of the primary concerns regarding HFT, the suggestion that HFTs decrease their trading activity or withdraw themselves from the market in highly volatile environments, does not appear from the analysis in this paper as the participation level of HFT firms is not materially different on the most volatile days compared to less volatile days. Although the Granger-causality test finds a significant bidirectional relationship between HFT activity and stock market volatility, i.e. increased levels of volatility being preceded by higher levels of HFT activity and vice versa, the study does not provide statistical evidence regarding causality in the more common sense, i.e. HFT exacerbating volatility or higher volatility increases HFTs' activity.

**Keywords:** Algorithmic Trading, High Frequency Trading, Stock Market Volatility, Nordic Stock Markets, EGARCH, Granger-Causality

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# List of Abbreviations

The subsequent table defines various acronyms and abbreviations that are used throughout the thesis.

| Abbreviation | Meaning |
|---|---|
| ADF | Augmented Dickey-Fuller |
| ARCH | Autoregressive Conditional Heteroscedasticity |
| ARMA | Autoregressive Moving Average |
| AUTD | Automated Trading Accounts |
| AT | Algorithmic Trading |
| EGARCH | Exponential Generalized Autoregressive Conditional Heteroscedasticity |
| GARCH | Generalized Autoregressive Conditional Heteroscedasticity |
| HFT | High Frequency Trading |
| HFTs | High Frequency Traders |
| OLS | Ordinary Least Squares |
| OMXC | Copenhagen Stock Exchange |
| OMXH | Helsinki Stock Exchange |
| OMXS | Stockholm Stock Exchange |
| O/T | Order-to-Trade ratio |
| SDR | Special Drawing Rights |
| VIF | Variance Inflation Factor |
| $VOL_{HL}$ | Volatility based on the logarithmic high-low range |
| $VOL_{SD}$ | Volatility based on the standard deviation of the daily returns |

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# 1 Introduction and Problem Discussion

The in recent years greatly increased presence of high frequency traders (henceforth HFTs) on the financial markets has attracted considerable attention from media, politicians, regulators and researchers. A debate with widely divergent opinions has emerged regarding the benefits and detriments of high frequency trading (HFT). Proponents of HFT argue that its presence in the market enables the discovery of mispricing, reduces transaction costs and increases market liquidity. However, opponents, mainly institutions and financial investors that do not utilize the benefits of HFTs, argue that the presence of HFTs destabilizes the financial markets and increases volatility. Moreover, the critics argue that the entrance HFT on the stock markets has created an unfair playing field.

Despite the great attention on this topic and the relevance for a large number of people and institutions, the academic research on HFTs' behavior and its implications for other market participants and financial markets is limited. A serious obstacle in conducting research on this topic is the limited data availability, which is mainly driven by two reasons. In the first place, as HFT is still lacking a generally accepted definition, classifying HFTs is difficult. In addition, the identity of the trader that originates an order cannot always be traced with absolute precision. This is a consequence of the fact that members of the exchanges have many accounts and some of the larger members allow sponsored access, i.e. other members trading on their behalf. Hence, even with an established definition of HFT, trading platforms would not be able to exactly distinguish HFTs from other algorithmic traders.[1]

Even though the precise characteristics of HFTs are not yet clearly defined, there are several features that are attributed to HFT firms. The US Securities and Exchange Commission (SEC) describes HFT firms as proprietary traders that use extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders; use co-location services[2] and private data feeds offered by exchanges to minimize latencies; have very short time-frames for establishing and liquidating positions; submit numerous orders to the markets

[1] Algorithmic traders are traders that use computer algorithms that automatically make certain trading decisions, submit orders, and manage those orders after submission, with limited or no human intervention (Hendershott, Jones and Menkveld, 2011).

[2] Co-locating refers to placing data servers in proximity to the trading venues in order to minimize latency to the trading systems.

that are often cancelled shortly after submission; and typically end the trading day in as close to a flat position as possible (SEC, 2010).

The existing research on this topic uses several different proxies for HFT activity and focuses predominantly on the US stock exchanges, London Stock Exchange and Deutsche Börse. As of February 21st 2012 no quantative study had been made on the Nordic stock markets that investigates the relationship between HFT and stock market volatility (Johansson, 2012). To the authors' knowledge, this is still the case prior to the completion of this paper. This study attempts to fill the gap by utilizing a unique dataset, provided by the OMX NASDAQ Nordic, that comprises a proxy for the fraction of the total market turnover that can be attributed to HFTs for three of the Nordic stock markets; the Copenhagen Stock Exchange (OMXC), Helsinki Stock Exchange (OMXH) and Stockholm Stock Exchange (OMXS).

The dataset used in this paper ranges from March 2010 to March 2012. During this time period, HFTs have become central market practitioners as they represented on average 13.6% of the total turnover on the three Nordic stock markets in March 2012.[3] Their presence more than tripled from March 2010 to March 2012 on each of the three markets.[4] However, despite the strong increase over these two years, HFTs' fraction of the total turnover appears to vary substantially from day-to-day, with an average variation of 19.1%.[5] Hence, the significantly increased presence of HFTs and the absence of any academic research on their trading behavior and interaction with stock market volatility on the Nordic stock markets accentuate the importance to shed more light on this phenomenon.

## 1.1 Purpose

The purpose of this paper is to investigate the contemporaneous and dynamic relationship between HFT activity and stock market volatility on the Stockholm Stock Exchange, the Copenhagen Stock Exchange and the Helsinki Stock Exchange, both on a daily and a monthly basis.

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[3] Based on the pooled monthly average on the OMXC (9.0%), OMXH (15.4%) and OMXS (16.4%).

[4] The average HFT activity in March 2010 was 4.1% and in March 2012 13.6%, resulting in an observed increase of 335% over the time period.

[5] Based on the pooled average day-to-day variation on the OMXC (21.7%), OMXH (20.3%) and OMXS (15.3%)

## 1.2 Scope and Delimitations

The empirical research in the paper is limited to the general index of three Nordic stock markets; the Copenhagen Stock Exchange, Helsinki Stock Exchange and Stockholm Stock Exchange. Additionally, driven by limited availability of data the paper examines the relationship between HFTs' overall trading activity and stock market volatility on an aggregate daily and monthly basis and does not distinguish between liquidity demanding and liquidity supplying activity. In order to be able to conduct an in-depth analysis, the paper focuses exclusively on the interaction between HFT and the volatility of the stock market and does not address the interaction of HFT with other market parameters.

## 1.3 Target Audience

The main audiences of this paper are individuals and organizations that strive to understand the complex nature of HFT and its interaction with stock market volatility on the Nordic stock markets. Moreover, the paper is directed to academics and researchers that seek to further build on the findings that are presented in this paper or intend to pursue a similar approach for future research in the topic of HFT in general or HFT's impact on volatility in specific.

## 1.4 Further Structure

Chapter 2 includes a background section that will serve as a framework for the continuing part of the study, in order to provide the reader with the relevant background information to comprehend the latter parts of the thesis. Chapter 3 provides the reader with an overview of previous research and relevant empirical findings in the field. Chapter 4 elucidates the utilized data. Chapter 5 focuses on the methodology and subsequently, chapter 6 presents the summary statistics for the variables used in the empirical part of the paper. The results of the empirical study and the analysis of the findings are presented in chapter 7 and finally, the results are discussed and concluded in chapter 8.

# 2 Background on Volatility and HFT

## 2.1 Volatility Outline

Volatility as a concept is a fundamental part of academic research and to contemporary financial markets. The importance of volatility can not be denied, as the phenomenon is a crucial factor in financial economics. Predominantly due to that pricing of financial assets and financial products are based on asset pricing models, like the hailed Black and Scholes option pricing formula, that are dependent on volatility as a variable. Further, valuation of derivative contracts depends on forecasts of volatility and investors that rely on mean variance theory likewise depend on volatility (Kalotychou and Staikouras, 2009).

Volatility is a normal consequence of stock market trading, which occurs through appearance of new information and subsequent actions by traders based on the new intelligence. The reaction initiated by additional market practitioners ensues in a chain reaction that alters the equilibrium level of the asset price and any further actions will be dependent on the degree of liquidity on the specific market. Ideally, stock prices should reflect the fundamental value of the listed companies. Therefore, when the volatility of the stock market is high, it indicates the existence of uncertainty about the true value of the respective companies. While volatility may create trading opportunities for speculators, for most market participants high volatility is undesirable and possibly detrimental. This is especially true whenever the level of volatility does not reflect the uncertainty about the true value of a company, because a certain group of traders exacerbates volatility as a result of their trading behavior (Groth, 2011).

Hence, as volatility is a vital concept for market participants and the behavior of HFTs and its relation to stock market volatility is an area that still lacks sufficient insights, it is important to get a better understanding of this phenomenon. The next section will provide an overview of the theoretical implications of the different strategies that are included in the umbrella term HFT.

## 2.2 HFT Strategies

HFT is a subset of algorithmic trading and refers to employing several specific trading strategies, rather than to a trading strategy in itself. To get a better understanding of the theoretical consequences of these strategies on market stability and price efficiency, it is important to separately analyze the key features of the predominant trading strategies that HFTs employ.

HFTs use algorithms to create orders according to a pre-programmed set of rules. The sophistication of those algorithms has increased substantially over time. The first-generation algorithms were pure trade algorithms, used to submit orders to the markets. Second-generation algorithms became much more advanced and were typically used to detect trading signals, which could then be executed by trade execution algorithms (Aldridge, 2012). A next step in the evolution of algorithms was the development of algorithms that include intelligent logic, that analyze market data itself and automatically adjusts the trading strategy to changes in the market to ensure the most profitable strategies. Especially this last and most advanced type of algorithms, the third-generation algorithms, is implemented by HFT firms in order to seek benefit from imbalances in the market and find pure arbitrage opportunities or high risk-adjusted returns.

The Securities and Exchange Commission (SEC) classifies the different trading strategies into four broad categories; passive market making, arbitrage, directional and structural (SEC, 2010). A key aspect that largely determines the degree of success of all the HFT strategies is the time needed to gather and process new information and appropriately respond to it by submitting specific orders to the market. Therefore, it is important to realize that not necessarily the trading strategy in itself allows HFTs to capitalize on market opportunities, but rather the possession of advanced technologies and quantitative techniques gives them an advantage over other market participants as this enables the firms to better identify and execute trading strategies. The key features and theoretical implications for the stability and price efficiency of the markets will be briefly discussed in the following subsections for each of the four predominant trading strategies employed by HFT firms.

#### *2.2.1 Passive Market Making*

Acting as liquidity provider, i.e. submitting non-marketable resting orders that provide liquidity to the marketplace at specified prices, is the most common HFT strategy. The primary sources of profit for these market making activities are the bid-ask spread and liquidity rebates or reduced transaction fees provided by the trading venues to submitters of liquidity-supplying buy or sell orders. The market making activities mimic the traditional role of market makers. However, with respect to market quality, passive liquidity provision has a major drawback. Unlike traditional market makers, electronic market makers among whom HFT firms are not under a fiduciary duty to submit limit orders to the market under all circumstances. As a consequence, HFTs have the possibility to temporarily withdraw themselves from the market during adverse market circumstances. The lack of a formal obligation to be on the bid and offer side could result in vanishing liquidity in times when liquidity is most needed; in times of market stress (Hendershott and Riordan, 2011). Hence, even though the liquidity of the markets could have increased and bid-ask spreads could have narrowed after the appearance of HFT firms in the market due to increased competition among market makers, a potential positive overall effect on market quality cannot be generalized to all specific circumstances.

### *2.2.2 Statistical and Pure Arbitrage Strategies*

In contrast to market making activities, trades necessary to execute arbitrage strategies are mainly demanding liquidity. In pursuing (statistical) arbitrage opportunities, HFTs seek discrepancies between correlated prices of products or markets. In market neutral arbitrage, the arbitrageur takes a long position in an instrument, which they perceive to have a relatively higher intrinsic value, while simultaneously taking a short position in an instrument they perceive to have a relatively lower intrinsic value. This strategy results in a market neutral position. When the respective valuation of the two instruments normalizes toward the expected direction, the position is liquidated and a profit is captured (Aldridge, 2010). Although the position is protected against market movements due to its market neutral nature, this arbitrage strategy contains the risk of unexpected movements or increased price discrepancies. In addition, if a perfectly correlated hedge instrument does not exist and therefore the hedged position is imperfect, the risk of an arbitrage position also comprises the volatility of the difference between the mispriced instrument's return and the hedge instrument's return (Pontiff, 1996). Moreover, the arbitrageur incurs transaction costs that reduce the attractiveness of the arbitrage opportunities. Although these transaction costs can be higher in more volatile markets, there are more arbitrage opportunities when prices are volatile, suggesting in general a positive interaction between volatility and liquidity demanding activity.

Other ways to capitalize on market inefficiencies are cross-asset pairs trading and cross-market arbitrage strategies. In cross-market arbitrage, the arbitrageur simultaneously buys an instrument in one market and sells the instrument in another market where the same instrument is valued higher. Cross-asset pairs trading arbitrage involves buying or selling a derivative that is priced too high or too low, respectively, relative to its underlying. Both these strategies typically have a beneficial effect on the quality of price discovery. Hence, even though these arbitrageurs may induce other market participants with adverse selection costs, generally they contribute to market quality by increasing price efficiency. Nonetheless, just as is the case for passive market making activities, the behavior of HFTs in extreme market circumstances is difficult to assess. As Shleifer and Vishny (1997) show in their theoretical model, professional arbitrageurs may avoid extremely volatile arbitrage positions, since the higher volatility exposes the firms to increased risk of losses and liquidity problems. As a consequence, the elimination of market anomalies may be less efficient in times of market stress.

#### *2.2.3 Structural Strategies*

Whether the aforementioned arbitrage strategies are overall beneficial or harmful for long-term investors is difficult to address and could vary depending on the type of investor and market conditions. However, from a perspective of fairness these arbitrage strategies are not directly concerning, since all market participants have the possibility to capitalize on the price discrepancies across markets and assets. More concerning are the differences in latency between private data feeds offered by trading venues and the consolidated data feed. When one firm obtains faster delivery of market data through either co-location arrangements or private data feeds, it could potentially profit by identifying market participants who submitted orders at stale prices, i.e. old prices that do not reflect the most recent information (SEC, 2010). In addition, this 'latency arbitrage,' i.e. receiving the data faster because of a special treatment, gives those firms an arbitrary comparative advantage relative to other market participants in predicting future market movements. Hirschey (2011) finds evidence for the hypothesis that HFTs' trades predict future buying by non-HFTs. However, the empirical evidence for a positive correlation between trading by HFTs and future trading by other market participants, based on data from the NASDAQ stock market, does not hold for trading around intraday news releases. Following this finding, Hirschey suggests that the predictive power is not driven by faster reaction to news announcements.

#### *2.2.4 Directional Strategies*

The fourth category of trading strategies covers directional strategies. Directional strategies refer to strategies in which a trader anticipates on intraday price movements into a specific direction. The most straightforward directional strategy comprises identifying instruments that have moved away from its fundamental value and establishing a position that anticipates on a return to the expected value. Anticipating on deviations from the perceived fundamental value by HFT firm is not different from the strategy of other market participants and may contribute to the quality of price discovery in an instrument and dampen price movements. However, there are other more concerning types of directional strategies, in which HFT firms attempt to exploit other market participants. One type of those strategies are order anticipation strategies, in which the order anticipators act as parasitic traders. They do not benefit price informativeness and do not improve market liquidity (Harris, 2003).

As discussed in section 2.2.1, HFT firms in their role as passive market makers typically provide liquidity to the market by submitting limit orders to the order book. But rather than having the intention the take the opposite side of the trade, HFT firms may attempt to capture a profit by trading alongside large institutional traders that are trying to passively accumulate or liquidate a large position. Bertsimas and Lo (1998) find that, in the presence of a trade completion deadline and temporary price impacts, the total cost of a market order can be minimized by breaking the order into smaller pieces. However, the opportunistic behavior of HFT firms, which try to identify the large orders made by institutional and thereby predict the directional price movement, affects the optimal dynamic execution strategy for institutional traders and possibly increases the total costs of their trades. In addition, it can exacerbate the price impact of large trades and hence, increase short-term volatility.

Second types of directional strategies that raise concerns are momentum ignition strategies. This refers to strategies in which traders act as price manipulators in order to change other market participants' opinions about instrument values. The firms engaging in these strategies may initiate a series of orders and trades in an attempt to ignite a rapid price movement. The trades may be real market trades or so-called 'wash trades', trades arranged with confederates to create artificial market activity (Harris, 2003). Even though market manipulation is illegal in most countries, it is very difficult to trace. Besides causing harm to other market participants, HFTs who employ these strategies may also hurt each other by triggering each other's algorithms. As a consequence, the manipulative strategies may drive asset prices away from their fundamental value and hence, aggravate price shocks and worsen price stability.

# 3 Overview of Previous Research

## 3.1 HFT and Market Quality

Even though HFT is attracting more and more attention and the literature base on algorithmic trading and HFT is expanding in a rapid pace, the existing research base on HFT is still relatively limited. Main reasons are the fact that HFT is a relatively new phenomenon and data that distinguishes HFTs' trading activity from other market participants is not widely available. The previous research in this to a large extent unexplored field discussed in this section consists of both published articles and working papers that are finished recently and are waiting to be published eventually. A majority of the academic papers in the field focus on the consequences of algorithmic trading in general or HFT specifically on market dynamics and certain market quality parameters and are mainly based on data from the US markets. The most prominent parameters being investigated are volatility, liquidity and price efficiency. Other aspects being investigated are profitability of HFT firms and activity of HFT traders under different market conditions.

### *3.1.1 Short-Term Traders*

One of the main characteristics of HFTs is the short average holding period of its positions. Several academic papers have investigated the behavior of short-term traders, already before the emergence of the HFT phenomenon. The suggestions derived from these papers may contrast with the classical market efficiency hypothesis that states that volatility is the result of new information being incorporated into market prices. De Long, Shleifer, Summers and Waldmann (1990) conducted their research before the algorithmic trading era and find that short investment horizons and noise trading may imply excess volatility and divergence of asset prices from their fundamental values in the presence of systematic misperception. Their model suggests that arbitrage trading can be seen as a response to noise trading rather than as trading on fundamental prices. From this perspective, predicting the pseudo signals that noise traders are expected to follow and bet against them more successfully could be a successful strategy to exploit traders that do not focus on fundamental values of assets.

Froot, Scharfstein and Stein (1992) also investigate short-term traders' behavior and focus in their research on the way in which speculators' trading horizons affect the nature of asset prices. The paper suggests that herding by short-term speculators may induce investment in information unrelated to fundamental values. The outcome of their research includes the finding that speculators with a short-term horizon may put too much emphasis on short-term information and as a consequence, their trading behavior lacks focus on stock fundamental information. Hence, Froot, Scharstein and Stein conclude that the presence of short-term speculators may decrease the informational quality of market prices and therefore cause deviations from the market efficiency hypothesis, potentially resulting in decreasing price stability and higher volatility.

Building further on the consequences of short-term traders' behavior on the informativeness of asset prices, Vives (1995) finds that the way private information arrives at market participants determines the market impact and deviation from the efficient market price. Vives' research points out that in case of concentrated arrival of private information, the deviation from the fundamental price increases through short-term traders' behavior, while the price informativeness is enhanced by traders with short-term horizons in case of diffused arrival of information.

Taken together, the findings of these academic papers on short-term traders, written before the algorithmic and HFT era, suggest that HFT can have both beneficial and harmful consequences for the informativeness of prices and the volatility of assets, depending on the pattern of private information arrival and the extent of herding among traders based on information unrelated to fundamental values.

### *3.1.2 Algorithmic Trading*

More recent research, focusing directly on algorithmic trading and HFT, also gained valuable insight in the effects of algorithmic trading, and more specifically HFT, on price efficiency and other market quality parameters. Chaboud, Hjalmarsson, Vega and Chiquoine (2009) focus in their research on the foreign exchange market and investigate among other aspects the relationship between algorithmic trading and volatility. Chaboud et al. focus on three currency pairs; euro-yen, euro-dollar and dollar-yen. Even though they provide evidence that algorithmic trades are more intercorrelated than non-algorithmic trades and therefore a higher proportion of algorithmic trading negatively influences the diversity, the researchers only find little evidence for a causal relationship between volatility of the market prices and the share of algorithmic trading out of total trading volume. Their empirical results, however not statistically significant, point toward a somewhat negative general relationship between the share of algorithmic trading and volatility, suggesting computerized trading generally increases price stability and dampens the exchange rate volatility.

Hendershott and Riordan (2009) and Groth (2011) also do not find an evident causal relationship between algorithmic trading and market price instability in their empirical research. The researchers focus on the German DAX30 index, which includes the thirty largest stocks when it comes to market capitalization, and cover the time periods from January 1st to January 18th 2008 and October 8th to October 12th 2007, respectively. Consistent with the findings of Chaboud et al., Hendershott and Riordan do not find evidence that algorithmic trading contributes to volatility in the market. What they do find in their analysis is that algorithmic trading tends to consume liquidity when bid-ask spreads are low and provide liquidity when bid-ask spreads are high, meaning that algorithmic trading generally prevented spreads of the DAX30 index from widening beyond a certain point. As a result, their findings indicate that algorithmic trading positively affects both price efficiency and market liquidity. Groth (2011) finds evidence in the same direction and suggests that the participation of algorithmic traders is not associated with higher levels of volatility. Moreover, Groth provides evidence that algorithmic traders do not withdraw themselves from liquidity providing activities during periods of higher volatility. Nonetheless, it has to be noted that the research results are limited to only five trading days in October 2007, a period that is not among the most volatile.

In addition to the findings of Hendershott and Riordan (2009) and Groth (2011) for the largest companies on the German stock market, Hendershott, Jones and Menkveld (2011) also provide empirical evidence for the hypothesis that algorithmic trading narrows spreads and suggests that algorithmic trading improves liquidity and also enhances price informativeness. Since it is not fully observable for the US stock market whether a particular order is generated by a computer algorithm, Hendershott et al. (2011) use the rate of electronic message traffic on the NYSE as a proxy for the amount of algorithmic trading in the market. Even though their research suggests that computerized trading has a positive effect on market quality, the research has some notable caveats that make it difficult to generalize the outcome to other periods than the sample period, from the end of 2002 until the end of 2006. Most important limitation is the fact that stock prices generally rose during the sample period and in addition did not experience highly turbulent phases. Hence, whether algorithmic trading is also beneficial for the market quality and price stability during more turbulent times and in declining markets remains an unanswered question for the time being.

### *3.1.3 High Frequency Trading*

Although the research focusing on algorithmic trading in general suggests favorable effects on market stability, liquidity and price efficiency, HFT as a subset of algorithmic trading has to be analyzed separately as it has different characteristics. The first theoretical model that specifically focuses on the impact of HFT on market quality parameters, rather than the impact of algorithmic trading in general, is constructed by Cvitanic and Kirilenko (2010). Their model assumes HFTs are uninformed traders that do not possess any superior information, which means their only advantage is the speed at which they can submit and cancel orders. The presence of an HFT firm in a market with otherwise low-frequency traders results in their model in a change in the distribution of transaction prices. Cvitanic and Kirilenko theoretically show that transaction prices are distributed more closely around the center and have thinner tails in case an HFT firm enters the market.

A majority of the subsequently written literature, most of which is based on empirical research, also suggests that HFTs' participation is overall beneficial for market quality. Brogaard (2010), who uses a dataset in which the trades of 26 main HFT firms are identified for 120 stocks listed on the NASDAQ and BATS exchanges, suggests that HFTs' activities are not detrimental to other market participants. Brogaard's extensive preliminary paper, later broken down into three separate papers, investigates HFTs' relationship with several characteristics of the overall market. The empirical study, with the time period under investigation being the years 2008 and 2009 and the trading days between February 22nd and February 26th 2010, finds that HFTs' overall daily participation does not seem to increase or decrease substantially when daily volatility levels change. Nonetheless, the paper finds that HFTs' liquidity supplying activity generally decreases when volatility increases whilst liquidity demanding activity increases for higher levels of volatility. After several additional tests, Brogaard concludes that HFTs' overall behavior may dampen intraday volatility and improve market quality of the US stock markets, through a positive contribution to liquidity and price discovery.

Other researchers who have provided evidence for a rather positive contribution of the presence of HFTs on traditional market quality measures are Hendershott and Riordan (2011), Martinez and Rosu (2011), Hasbrouck and Saar (2010) and Castura, Litzenberger, Gorelick and

Dwivedi (2010). Hendershott and Riordan (2011) utilize the same dataset as Brogaard and find that HFTs typically trade in the direction of reducing transitory pricing errors. This finding holds both for normal and volatile days in a time period of relatively high market turbulence, the years 2008 and 2009. Martinez and Rosu (2011) model HFTs' liquidity demanding activities and assume that HFT firms are informed traders, in line with the findings of Hendershott and Riordan (2011). Therefore, they assume HFT firms trade in the right direction. As a result, their theoretical model suggests that fast responding HFT firms make markets extremely efficient and do not destabilize markets, as long as there are market makers ready to provide liquidity during volatile periods.

Hasbrouck and Saar (2010) conduct empirical research on low-latency trading and find that the presence of firms that respond to market events within milliseconds, the hallmark of HFT firms, improves short-term volatility, bid-ask spreads and depth in the limit order book. Their findings, based on data from NASDAQ, hold for both periods with normal market conditions and during a period of declining prices and increased uncertainty.

From a more general perspective, investigating the development of market characteristics over time, Castura, Litzenberger, Gorelick and Dwivedi (2010) show that the emergence of HFT has coincided with a significant decrease in bid-ask spreads and increased liquidity at the inside of the order books on US exchanges. However, these findings are subject to noise and other changes in the marketplace than the emergence of HFT firms can have contributed to the decrease in spreads and increased liquidity.

Contrary to the typically positive findings of most conducted research regarding HFT and its impact on market quality, Jovanovic and Menkveld (2010) and Kirilenko, Kyle, Samadi and Tuzun (2011) find somewhat more concerning outcomes. Jovanovic and Menkveld develop a theoretical model and also conduct empirical research to shed light on the consequences of HFT. Their theoretical model shows ambiguous welfare effects when HFT firms enter the market. On the one hand, a pre-existing adverse selection problem can be solved by informed market makers, which HFT firms are assumed to be, but on the other hand the HFT firms can exacerbate an existing adverse selection problem. To be more specific, when HFT firms are expected to have faster access to the same information as late-arriving investors, the model suggests that HFT reduces welfare. However, when assuming late-arriving investors have better or new information relative to HFT firms that act as a middleman in the market, welfare is expected to rise due to price quotes that reflect the available information more accurately. The validity of this theoretical outcome further depends on the willingness of HFTs to provide liquidity, i.e. produce price quotes, rather than consuming liquidity, which is in turn dependent of fee structures and regulations of the stock exchanges.

Jovanovic and Menkveld's empirical research is based on data from the Chi-X, a trading platform catering to the demands of HFTs. It compares market quality of Dutch index stocks before and after the entrance of a large HFT firm, acting as middleman, to the Chi-X trading venue. The researchers find evidence for their hypothesis that the middlemen in the market are better informed than the average investor, following from the observation that they react faster to new information, and then trade in the right direction to lock in a profit in addition to the bid-ask spread. These findings contrasts to the findings of Hirschey (2011) regarding the NASDAQ stock market, who did not find evidence that HFTs profit by responding faster to new information. The empirical findings of Jovanovic and Menkveld confirm the hypothesized reduced welfare effects for other market participants of anticipation strategies in which the HFT firm act as a parasitic trader. However, the paper does not find any evident correlation between volatility and HFTs.

Kirilenko, Kyle, Samadi and Tuzan (2011) analyze HFTs behavior in the E-mini S&P 500 futures market during the flash crash on May 6th 2010. Even though they conclude that HFTs did not ignite the flash crash, their findings suggest that HFTs' behavior enhanced price volatility. After initially supplying liquidity and building a long position just before the sharp market decline, HFTs started to reduce their inventories. Based on the observed behavior of HFTs during the flash crash, the authors suggest that when HFTs rebalance their positions during volatile environments, they may compete for liquidity with other market participants and amplify price volatility.

Overall, a majority of the existing research suggests that HFT does not exacerbate volatility. However, it is evident that the current stream of research is far from exhaustive. As a result of the absence of adequate data and precise methods to estimate HFTs' fraction of the total trading volume, most of the research is based on incomplete datasets or datasets that only cover very limited time spans. Moreover, the research mainly focuses on the US stock markets. There has not been shed much light onto the behavior of HFTs on the Nordic stock markets, stressing again the relevance of the analysis for the Nordic stock markets in this paper.

## 3.2 Determinants of Stock Market Volatility

When analyzing the relationship between HFTs' trading behavior and stock market volatility, it is vital to take into account that there are other factors influencing the stock market volatility and possibly also HFT activity. A potential relationship between HFT and volatility can be caused by other underlying factors that drive both processes. Therefore, it is of great importance to comprehend the determinants of stock market volatility, in order to be able to control for these variables in the empirical study.

The research on the origins of stock market volatility is extensive. Nevertheless, the findings are not entirely in accordance regarding the determinants of stock market volatility. The strands of literature that examine the determining factors of stock market volatility focus mainly on two broad categories: macroeconomic factors underlying the stock market volatility and market characteristics as explanatory factors for volatility. Schwert (1989a and 1989b) has analyzed the volatility of the American market for the time period from 1834 to 1987. Over this extensive time frame the author finds weak evidence for a relationship between the volatility of macroeconomic variables and illustrates an inverse relationship between volatility and recessions.

Moreover, Liljeblom and Stenius (1997) conduct a similar long-term analysis of stock market volatility for the time period from 1920 to 1991, but focus on the Finnish market instead of the American market. Their findings regarding a relation between conditional stock market volatility and macroeconomic volatility are surprisingly strong as compared to the findings on the US data, reinforcing that macroeconomic fluctuations are suitable indicators for stock market volatility and hence, it is essential to control for these factors when analyzing the relationship between HFT and volatility.

In the next subsections the most commonly used explanatory macroeconomic and market variables in present research on volatility are addressed. The volatility determinants are divided into three sub-sections; macroeconomic policy variables that depend on domestic fiscal and monetary policies, factors that measure the stage in the business cycle and market activity measures.

### *3.2.1 Macroeconomic Policy Uncertainty*

The link between stock market behavior and fluctuations in interest rates has been under scrutiny in previous research. In research conducted by Blanchard (1981) and Christie (1982), the authors present findings that interest rate levels and the variance of equity returns are strongly positively correlated. Elementary economics theory states that the money supply is significantly positively correlated with inflation levels and is negatively correlated with the interest rate level on the domestic market. Thus, the monetary policy undertaken by the ruling regime in a country may influence the volatility on the domestic stock market. Furthermore, the characteristics of exchange rate volatility can have a significant effect on the trade balance of nations, risk management decisions and portfolio strategies by private, HFT and institutional investors. Hence, there may be an implied relationship between exchange rate levels and volatility of the stock market. Research in the topic has predominantly been executed in emerging markets where exchange rates tend to be excessively volatile compared to stable economies (Walid, Chaker and Masood, 2011; Tahir and Keung, 2010). The authors illustrate that stock market volatility is positively correlated to exchange rate fluctuations. Thus, investors are eligible to forecast the stock market volatility through analyzing exchange rate behavior.

### *3.2.2 Business Cycle Factors*

Corradi, Distaso and Mele (2009) find evidence for a strong correlation between business cycle patterns and stock market volatility. The authors develop a no-arbitrage model where unobservable and macroeconomic factors are connected to stock market volatility. Evidence is introduced that industrial production is an explanatory variable for stock market volatility and further that inflation has little influence on the volatility.

Brandt and Kang (2004) also examine the relationship between business cycle indicators and the volatility of the stock market. Their research verifies that the pattern of the business cycle and stock market volatility is negatively correlated. Their study shows that in recessions the volatility increases, whereas volatility decreases during expansionary periods. Moreover, the research conducted by Corradi et al (2009) rests its hypothesis on the findings of the previously described research. The authors utilize the Consumer Price Index (CPI) and the Industrial Production Index (IPI) to test the relationship. As the CPI represents a statistical approximation of the price level of consumer goods and services it serves as a suitable measure for the market patterns and is commonly employed as an indicator of the inflation level. Further, the IPI functions as an appropriate economic indicator as it measures the manufacturing output of a country. Hence, the index represents the foundation, along with other constructional indexes, for fluctuations in the domestic production output over a business cycle (SCB, 2012). The practice of using inflation and domestic output as determinants for stock market volatility is appraised due to its association to the overall stability of the economy in the sense that volatility of the stock market is dependent on real economic variables.

Davis and Kutan (2003) study volatility persistence from an international viewpoint, using stock market and inflation data from 13 developed countries. Their study illustrates only a week predictive power of inflation volatility on stock market volatility. However, existing research made on the topic by Engle and Rangel (2005) present results of the contrary. In the study the authors use the Spline-GARCH model on the Turkish and Canadian market and provide evidence that the level of inflation volatility has a high predictive power on stock market volatility. Further, the study shows that the emerging Turkish market experiences higher levels of stock market volatility than the more developed market of Canada as markets with higher inflation experience higher levels of volatility. Moreover, in the study conducted by Saryal (2007), the authors' findings support the result of the research made by Engle and Rangel. Saryal studies data from the Canadian and Turkish market and likewise shows that inflation volatility recommences to be an important determinant of stock market volatility.

Additionally used measures for the economic environment in a country is the growth in real GDP and real GDP per capita. Both measures serve a good proxy for the economic development over a long time period, as the measures are inflation adjusted and adjusted for the terms of trade. In a study made by Levine and Zervos (1998) the authors investigates if stock market volatility and liquidity are correlated with future and current rates of economic growth for 47 countries between 1976 through 1993. As a proxy for the economic growth the authors utilize real GDP per capita growth, growth in productivity, real physical capital stock growth per capita and a ratio between GDP to private savings. The study suggests a weak negative relationship between economic growth and market volatility.

#### *3.2.3 Market Activity*

The stock market turnover is a good indicator of the development of the stock market activity over time. The usage of the stock market turnover as a determinant of volatility is of great importance due to its ability to illustrate the characteristics of the market unrelated to the actual size of the market. In a study by Xiao and Brooks (2010) the authors explore the relation between stock market volatility and daily order volume on the Australian Stock Market. The article proves that trading volume has high explanatory power on stock volatility, suggesting that the greater the volume the greater price movements in the market. Moreover, in a study by Chuang, Hsiang and Susmel (2011) the authors investigate the contemporaneous and causal relationship between stock market volatility and trading volume on the ten largest stock markets in Asia. On six of ten stock markets the authors find a positive contemporaneous relationship between trading volume and the volatility of stock market returns. However, they find a negative relationship between trading volumes and return volatility on two of the stock markets studied.

Taking it all together, including macroeconomic and market variables as additional explanatory variables in the empirical research is vital to avoid invalid inferences from the empirical analysis. Hence, in order to control for macroeconomic policy uncertainty, the stage in the business cycle and the market activity, several variables are used as proxy for each of the categories and will be included in the empirical analysis.

# 4 Data Description

The dataset that identifies HFTs' activity extends from March 2010 to March 2012 and consists of daily and monthly observations for the stock markets of Stockholm, Copenhagen and Helsinki. The dataset that includes the market index observations and the macroeconomic variables that may be related to the volatility of the stock markets has a corresponding time range. The time period of the study is arranged to two years as it enables to cover the development of HFT and its interaction with volatility over a recent time period. Additionally, since HFT is a relatively recent phenomenon, HFTs' fraction of the total market turnover on the Nordic stock markets was limited before 2010. As a result, finding a statistically significant relationship between HFT and market volatility is less likely for earlier years than for the past two years, in which HFT firms have been strongly represented.

This section describes the method used by the NASDAQ OMX to derive the proxy for HFT activity and also gives a description of the market variables and macroeconomic variables used in the empirical research.

## 4.1 Proxy for HFT Activity

The proxy for HFTs' trading activity on the Stockholm Stock Exchange (OMXS), the Copenhagen Stock Exchange (OMXC) and the Helsinki Stock Exchange (OMXH) is based on two distinct datasets provided by NASDAQ OMX Nordic in Stockholm; a proxy of HFTs' fraction of the market turnover with a daily frequency and a separate dataset that has a monthly frequency and proxies HFTs' fraction of the total monthly market turnover on the respective stock exchange. The proxy constructed by NASDAQ OMX is based on the share of the total market turnover of traders with purely automated trading (AUTD) accounts with an order-to-trade (O/T) ratio higher than 10 and identifies the approximate activity of HFTs for each of the stock exchanges individually. As the dataset identifies the activity of HFTs for the aggregate stock market the proxy serves as a suitable tool for generalization as it covers all the traded equities on the respective market.

The NASDAQ OMX Nordic distinguishes between three different user categories with different trading rights and levels of market access. The first category comprises exchange traders that are members of the NASDAQ and authorized to trade on the market. The second category has incremental rights and consists of direct market access (DMA) clients that are entitled to electronically route orders to the stock exchange system. The third category is the most advanced and consists of algorithmic trading firms that are entitled to trade through automated trading facilities in the form of placement, change, or cancellation of orders in the order book. Within this algorithmic trading category, firms can establish special automated trading accounts, AUTD accounts, which are exclusively used for automated trading. Hence, common execution algorithms are not eligible for these accounts (NASDAQ OMX Nordic, 2011). The usage of the AUTD accounts entitles the firms to a discount when trading, which is particularly appealing to short-term traders who make large numbers of trades during a trading day; a common characteristic of HFTs. The further refinement used by NASDAQ OMX Nordic, in order to derive a suitable proxy for HFT activity on the exchanges, is classifying only firms with AUTD accounts that have an O/T ratio of over 10. This is an effective refinement, since the submission of numerous orders that are often cancelled shortly after the submission is also an important feature of HFT firms. Due to the technological edge HFTs have over other market participants, they can respond quickly to changing market circumstances, which in turn leads to large quantities of orders being entered at great speed. Most of these orders remain unexecuted or are cancelled shortly after entering, resulting in O/T ratios that can easily surpass 100:1 (AFM, 2010). The O/T ratios of other market participants are substantially lower and do typically not exceed the delineation criteria of 10 orders per trade in the longer run.

When comparing the activity of HFTs as appears from the dataset used in this paper with the activity of HFTs that appears from the by Brogaard (2010) and Hendershott and Riordan (2011) used dataset, it is evident that, according to the proxies used for both datasets, the presence of HFT is significantly lower on the Nordic markets than on the US markets. Brogaard (2010) finds that HFTs were on average involved in 68.5% of the market turnover in 2008, 2009 and February 22nd to February 26th 2010, whereas the average participation of HFTs in the dataset used in this paper is 8.0%.[6] However, in addition to different time periods, the used proxies differ substantially from each other when it comes to identifying HFT firms. The dataset based on the US market distinguishes messages from 26 firms that were identified by the NASDAQ as firms engaging primarily in HFT. For many of these firms, however, a substantial portion of their total trade activity consists of ordinary trades with longer holding periods and

[6] 8,0% is the average of the fraction of total market turnover on the Stockholm Stock Exchange (10,8%), the Copenhagen Stock Exchange (4,9%) and the Helsinki Stock Exchange (8,3%).

trades made through common execution algorithms and therefore also includes other than purely automated trades. In addition, the dataset used by Brogaard (2010) and Hendershott and Riordan (2011) comprises 120 randomly selected stocks that have a five times higher average market capitalization than the average market capitalization of all the listed stocks on the NYSE and NASDAQ.[7] Still, even though the proxies are different, the presence of HFTs on the Nordic stock markets can be assumed to be lower than on the US markets. A plausible partial explanation for the lower HFT-ratio on the Nordic markets is the non-existence of a National Best Bid and Offer (NBBO)-system. As such a system requires that brokers must assure its market practitioners the best obtainable ask or bid price it enables HFT firms to abuse the structural weaknesses in the US market (SEC, 2010).

Altogether, although the method used by the NASDAQ to identify HFT firms does not allow for an exact measure of HFT activity, the dataset is expected to give an accurate estimation of the fraction of trading turnover that is attributable to HFTs on the Nordic markets. To the authors' knowledge, the dataset that forms the foundation of this paper is currently the most accurate proxy for HFT activity on the Nordic stock market provided to researchers.

## 4.2 Market Data

In addition to the dataset that identifies HFTs' activity on the three Nordic stock markets, daily market turnover, high and low prices and adjusted closing prices for the general indexes of the three stock exchanges are obtained from the NASDAQ OMX Nordic for the corresponding trading days. As the HFT proxy is provided on an index basis the market variables are likewise index based in order to ensure a consistent analysis. The NASDAQ OMX Nordic calculates the indexes both as price indexes (PI) and total return (GI) indexes, where in the former cash dividends are not reinvested in the index and the latter reflects the true performance of the index. As this paper focuses on the performance of stock price movements, the data is obtained from the price indexes. Moreover, since the HFT proxy is expressed as percentage of the total market turnover for the given time periods, the total turnover of the market is included as well.

[7] The activity of HFTs is known to be substantially higher in larger, more liquid stocks (Hendershott and Riordan, 2011).

## 4.3 Macroeconomic Variables

In addition to market variables, the empirical study accounts for macroeconomic variables in analyzing the relationship between HFT and stock market volatility. The control variables are used as a proxy for macroeconomic factors that affect the volatility of the stock markets. The first set of variables comprises the variables used to control for macroeconomic policy uncertainty; the natural logarithm of the money supply (M2), the volatility of the interest rate and the volatility of the exchange rate. In order to account for fluctuations in the exchange rate level of the Swedish krona, the Danish krona and the euro (for the Finnish market), the exchange rate of the domestic currency to the SDR[8] is included as a variable in the regressions. As the SDR can be exchanged for other currencies and the IMF updates the exchange rate every twenty minutes during trading days, it serves as a good measure for the value of the domestic currencies and as basis to determine the exchange rate volatility. To estimate the interest rate volatility, the three-month inter-bank lending rate for the respective country serves as basis and is obtained from Datastream, as well as the data for the aggregate amount of money and close money substitutes within a country (M2).

The data for the macroeconomic variables used as business-cycle indicators, inflation rate volatility, terms of trade (TOT) volatility and industrial production (IP) volatility, is also obtained from Datastream. To estimate the inflation volatility, the consumer price index (CPI) for the respective country is used as basis. The industrial production index is utilized as an indicator of the economic output, and used as a proxy for the GDP of the countries due to the availability of the data on a suitable frequency level and its sensitivity to fluctuations in the GDP level. Finally, the volatility of the terms of trade, which denotes the price of a country's exports in terms of its imports, is estimated from the monthly changes in the terms of trade index.

[8] The SDR is an international reserve asset, maintained by the IMF. The value of the asset is determined by four international key currencies: the euro, dollar, yen and the pound sterling. For 2011 to 2015, the currency basket is represented for 37,4% by the euro, for 9,4% by the Japanese yen, for 11,3% by the British pound sterling and for 41,9% by the US dollar (IMF, 2012)

# 5 Methodology and Variable Definitions

The volatility of the stock market may affect the incentive of HFTs to trade as it has an impact on both the risk of holding a position and the existence of profitable opportunities. However, HFTs' trading activity could also have an impact on market volatility. In this paper several empirical tests have been conducted to examine the interaction between the activity of HFTs and stock return volatility on the stock markets of Stockholm, Copenhagen and Helsinki. In order to get a better understanding of both the contemporaneous and the dynamic relationship between the two variables, the empirical study in this paper analyzes the relationship both for daily and monthly time frames. This section provides a description of the employed regression models and methods used to estimate the research variables incorporated in the different empirical tests.

## 5.1 Volatility Measures

A variety of proxies for stock market volatility are used in the existing academic literature. In this paper several widely used methods to estimate volatility are employed. Using different approaches to measure volatility is useful to gain insight into the sensitivity of the regression output and also to increase the reliability of the inferences. For the monthly analysis two different volatility estimators are used. The first method to estimate the volatility of the stock markets is based on continuously compounded daily returns of the stock market whereas the second method is based on the daily logarithmic high-low range of the stock indexes. The daily adjusted closing prices have been used to estimate daily returns, using the following formula:

$$R_t = \ln\left(\frac{I_t}{I_{t-1}}\right) \times 100 \tag{1}$$

where $R_t$ denotes the logarithmic daily percentage return on trading day $t$ and $I_t$ and $I_{t-1}$ denote the daily value of the stock market index on two successive trading days. The monthly realized volatility is then defined as the within-month standard deviation of the continuously compounded daily returns, calculated as follows:

$$VOL_{\mathrm{SD}m} = \left[\frac{1}{(n-1)} \sum_{t=1}^{n} (R_t - \mu_m)^2\right]^{0,5} \tag{2}$$

$$\text{with } \mu_m = \left(\frac{1}{n}\right) \sum_{t=1}^{n} R_t \tag{3}$$

where $VOL_{SDm}$ denotes the stock market volatility in month *m,* based on the standard deviation of the daily returns, $n$ is the number of trading days in a month and $\mu_m$ is the average stock market return in month *m.* [9]

The second method to estimate market volatility is based on the logarithmic range between daily high and low prices, where the log-range is defined as the first logarithmic difference between daily high and low values. The applied formula to derive the monthly volatility from intraday fluctuations is as follows:

$$VOL_{\mathrm{HL}m} = \left(\frac{1}{n}\right) \sum_{t=1}^{n} [\ln(H_t) - \ln(L_t)] \tag{4}$$

where $VOL_{\mathrm{HLm}}$ denotes the stock market volatility in month *m,* based on the logarithmic daily high-low range, $n$ is the number of trading days in a month, $H_t$ denotes the highest value on trading day $t$ and $L_t$ denotes the lowest value. [10]

The high-low range based volatility estimations was first introduced by Parkinson (1980), who demonstrated that the daily logarithmic high-low range is five times more efficient than the squared daily close-to-close return. Correspondingly, Andersen and Bollerslev (1998) and Alizadeh, Brandt and Diebold (2002) find evidence that the range-based volatility estimator is highly efficient and robust, compared to several alternative proxies of volatility that are popular in the existing academic literature. An important advantage of this measure relative to other popular volatility proxies, among which the other proxy used in this paper, is that the variance of the measurement errors associated with the range-based model is proven to be significantly lower. This is explained by the fact that stock prices can fluctuate widely throughout the trading day but the closing price could still be close to the opening price and therefore, the range-based estimator better reflects the intraday price variations. However, as the range is sensitive to outliers it is beneficial to also estimate volatility based on the squared daily close-to-close return.

In order to obtain estimates of the monthly volatility of the macroeconomic variables used as control variables in the regressions, the same procedure as in equation (2) is used for the

[9] Using the standard deviation of stock returns as a proxy for stock market volatility was previously used by among others Canina and Figlewski (1993) and Balaban, Bayar and Faff (2006).

[10] Alizadeh, Brandt and Diebold (2002) and Kyröläinen (2008), among various others, also use the log-range based measure to estimate market volatility.

daily observable variables; interest rates and exchange rates. However, since most of the macroeconomic factors incorporated in the regression can only be observed on a monthly basis, their volatility is estimated by following the procedure developed by Davidian and Carroll (1987). This procedure is similar to the widely used autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982) and estimates the conditional volatility of the monthly change $R_m$, given the information available before month $m$. The procedure consists of three consecutive steps. First, the 12th-order autoregression for the change is estimated by employing the following autoregressive model:

$$R_m = \sum_{i=1}^{12} \alpha_i D_{im} + \sum_{j=1}^{12} \beta_j R_{m-j} + \varepsilon_m \tag{5}$$

where $R_m$ denotes the logarithmic monthly percentage change in month $m$, $D_{im}$ denotes a dummy to allow for different monthly mean returns and $\varepsilon_m$ is the error term for month $m$, a white noise process with zero mean.

Subsequently, the same method is used to estimate the 12th-order autoregression for the absolute values of the errors $\varepsilon_m$. This autoregression also includes a dummy as in equation (5), in order to allow for different monthly standard deviations, and is estimated by the following equation:

$$|\hat{\varepsilon}_m| = \sum_{i=1}^{12} \gamma_i D_{im} + \sum_{j=1}^{12} \delta_j \hat{\varepsilon}_{m-j} + u_m \tag{6}$$

where $|\hat{\varepsilon}_m|$ denotes the absolute value of the prediction error for month $m$ as derived from equation (5), $D_{im}$ denotes the dummy that allows for different monthly standard deviations and $u_m$ is the error term. The fitted values, i.e. the predicted values from the second regression, estimate the conditional standard deviation of $R_m$.[11] In order to derive the monthly conditional volatility, the estimated fitted values from the second autoregression are adjusted by the term $(2/\pi)^{-0.5}$.[12]

The same volatility measure has also been used by among others Koutoulas and

[11] The fitted values are obtained by subtracting $u_m$ from $|\hat{\varepsilon}_m|$.

[12] Since the expected value of the absolute error, $E|\hat{\varepsilon}_m|$ appears to be lower than the standard deviation from a normal distribution (Schwert, 1996).

Kryzanowski (1996) to examine the role of conditional macroeconomic factors in an arbitrage pricing model and Kearney and Daly (1998) to investigate the causes of stock market volatility in Australia. Davidian and Carroll (1987) show that this measure of conditional volatility is more robust than a volatility measure based on the actual standard error of equation (5). In this paper, the method is used to estimate inflation volatility, industrial production volatility and the volatility of the terms of trade index.

### 5.2 Monthly Contemporaneous Relationship between HFT and Volatility

As a first step to assess the relationship between HFT and stock market volatility, HFTs' fraction of total trading volume is plotted against the estimated volatility, sorted from low to high. Demonstrating a general relationship between both variables, however, is not sufficient to be able to draw any legitimate conclusions, since the co-movement of both variables could be the result of an underlying third variable that drives both processes. In section 3 several variables that previously have been proven to affect stock market volatility have been discussed. In order to control for these variables that are related to volatility and possibly also to HFT activity they are included in the regressions as additional regressors.

As most of these control variables are only observable on a monthly basis, the first sets of regressions are based on the average monthly fraction of the total market turnover attributable to HFTs. It must be noted that the average is based on a separate dataset that estimates HFTs' activity based on the total monthly market turnover and therefore differs somewhat from the average daily activity of HFTs in a month. The monthly dataset identifies HFT activity on the three Nordic stock exchanges for a time span of 25 months, from March 2010 to March 2012, and therefore consists of a relatively small number of observations. As a result, the final regression model is built by adopting a strategy of sequential estimation, in order to conserve the degrees of freedom and statistical power of the model.

To derive the final regression model, three successive sets of regressions are conducted. The regressions conducted as first include the variables that are used as a proxy of the effect of macroeconomic policy uncertainty on stock market volatility; volatility of the exchange rate, volatility of the interest rate and the natural logarithm of the money supply. After testing the impact of these macroeconomic policy variables, the regression has been augmented first with the three business-cycle indicators, i.e. inflation volatility, industrial production volatility and terms of trade volatility, and finally with the variable that identifies market activity; the natural logarithm of the market turnover. After each successive set of regressions, the regressors that are found to be statistically significant at the 10% level are remained in the model, whereas the regressors that have been consistently insignificant are excluded in subsequent regressions. The regressions are conducted separately for both volatility measures ($VOL_{\mathrm{HL}}$ and $VOL_{\mathrm{SD}}$) as dependent variable and also both for the panel data in which the data of the stock exchanges is pooled and for each of the stock exchanges individually. The following least-squares regression model is estimated:

$$VOL_{\mathrm{HL}im} = \alpha + \beta\,\mathbf{M}_{im} + \gamma\,\mathbf{B}_{im} + \theta\,\mathbf{A}_{im} + \delta\,\mathrm{HFT}_{im} + \varepsilon_{im} \tag{7a}$$

$$VOL_{\mathrm{SD}im} = \alpha + \beta\,\mathbf{M}_{im} + \gamma\,\mathbf{B}_{im} + \theta\,\mathbf{A}_{im} + \delta\,\mathrm{HFT}_{im} + \varepsilon_{im} \tag{7b}$$

where $\mathbf{M}_{im}$ denotes the set of three variables that are used as a proxy for macroeconomic policy uncertainty for stock exchange $i$ in month $m$, $\mathbf{B}_{im}$ denotes the three business-cycle indicators, $\mathbf{A}_{im}$ denotes the market activity as measured by the total stock market turnover and $\mathrm{HFT}_{im}$ denotes HFTs' fraction of the total turnover in the respective month.

An additional procedure is followed in order to ensure the reliability of the final model and avoid spurious regression results. First, the final regression is repeated with an additional variable that captures a linear time trend in the data. Subsequently, a lagged variable of the volatility measure is included in the model, which makes it an autoregressive (AR) process, in order to control for potential remaining serial correlation in monthly volatility.

### 5.3 Daily HFT Activity and Conditional Stock Market Volatility

In addition to the monthly analysis for the time period from March 2010 to March 2012, the relationship between HFT and stock market volatility on each of the stock markets is also investigated on a daily basis for the same time span. As daily stock market volatility appears to be persistent over time and in contrast to the analysis based on a monthly frequency no macroeconomic determinants of volatility can be included to effectively capture the serial correlation, the used methodology to analyze the relationship on a daily basis differs from the method used for the monthly analysis. Instead of first estimating the volatility of the stock market and then assessing the relationship between volatility and HFT activity, HFTs' fraction of total trading is included directly into the variance equation of the employed exponential GARCH

(EGARCH) model as an explanatory variable.

The EGARCH model is developed by Nelson (1991) and is an extension of the autoregressive conditional heteroscedasticity (ARCH) model that was first introduced by Engle (1982) and the generalized ARCH (GARCH) model, developed by Bollerslev (1986). The ARCH model was suggested by Engle as an alternative to the standard time series models. It is well known that volatility is persistent for short time horizons and high volatility tends to continue for a while after a period of increased volatility. The serial correlation of volatility is taken into consideration in the ARCH models, in which the (conditional) variance is a function of lagged squared error terms (Campbell, Lo and MacKinlay, 2010). Therefore, the model allows the conditional variance to be substantially affected by possibly large squared error terms from previous periods.

The GARCH model is an extension to the ARCH model and includes in addition to lagged squared error terms also lags of the conditional variance in the model, which gives it the virtue that the number of parameters required to model persistence in volatility is reduced. The EGARCH model is a further extension and builds in a directional effect of price movements on conditional variance. An important benefit of the model is that it can distinguish between positive and negative returns and consequently captures potential asymmetry in volatility with respect to the direction of the returns. Hence, it has a better fit than the symmetric GARCH model for almost all financial assets (Alexander, 2009). The in this paper employed EGARCH(1,1) model incorporates one lagged variance term and one lagged residual term. The conditional mean and conditional variance are respectively estimated by the following equations:

$$r_t = a + b\, r_{t-1} + \varepsilon_t \; where \; E_t(\varepsilon_t) = 0 \; and \; E_{t-1}(\varepsilon_t^2) = \sigma_t^2 \qquad (8)$$

$$\log(\sigma_t^2) = \omega + \alpha \log(\sigma_{t-1}^2) + \beta \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + \theta \log(Turnover_t) + \varphi\, HFT_t \qquad (9)$$

where $\varepsilon_t$ denotes the unexpected return for trading day $t$, with an expected value of zero and a time varying conditional variance, $\varepsilon_t^2$ denotes the conditional variance as it is a one period ahead estimate for the variance based on all relevant past data, $Turnover_t$ denotes the total stock market turnover and $HFT_t$ denotes HFTs' fraction of the total stock market turnover.

The variance equation is dependent on three lagged terms; parameter $\alpha$ measures the persistence in conditional volatility, parameter $\gamma$ the symmetric effect of the model, i.e. the GARCH effect, and parameter $\beta$ the asymmetry in volatility. If the model is symmetric, parameter $\beta$ is equal to zero. If positive shocks with respect to the market return generate less volatility then negative shocks, $\beta$ is negative. When $\beta$ is larger than zero it implies that positive shocks have a more destabilizing effect than negative shocks.

### 5.4 Granger Causality Test

In order to analyze the dynamic relationship between HFTs' daily participation level and stock market volatility, the by Granger (1969) proposed time-series data based approach is used. The test states that if variable $x$ is useful in forecasting variable $y$ and increases the accuracy of the prediction of $y$ with respect to a forecast in which only past values of $y$ are included, $x$ is said to Granger cause $y$. However, it is important to realize that if the test finds evidence for Granger-causality, i.e. statistically significant F-statistics for lagged values of variable $x$, it does not mean that $x$ causes $y$ in the more common sense of the term but it only indicates that $x$ precedes $y$.

Granger-causality is tested for both directions; a change in HFTs' fraction of the market turnover preceding an increase or decrease of stock market volatility and a change in the volatility of the stock market preceding an increase or decrease in HFTs' activity on the next trading day. Granger-causality is estimated using the following equations:

$$VOL_t = \omega_1 + \sum_{i=1}^{p} \delta_i \, VOL_{t-i} + \sum_{j=1}^{q} \vartheta_j \, HFT_{t-j} + \mu_{1t} \tag{10}$$

$$HFT_t = \omega_2 + \sum_{i=1}^{n} \beta_i \, HFT_{t-i} + \sum_{j=1}^{n} \gamma_j \, VOL_{t-j} + \mu_{2t} \tag{11}$$

where $\mu_{1t}$ and $\mu_{2t}$ are disturbances that reflect variations over time beyond that attributable to past movements, $HFT_t$ denotes HFTs' fraction of the total market turnover on trading day $t$ and $VOL_t$ denotes the conditional daily volatility. The Granger-causality test is conducted for up to 3 lags, meaning $p$, $q$, $m$ and $n$ can assume values up to 3. The null hypothesis implies that $\gamma_j$ and $\vartheta_j$ (with $j$=1,2,3) are all equal to 0, i.e. there is no causality.

# 6 Summary Statistics

## 6.1 Monthly Summary Statistics

The summary statistics of the variables used in the regressions on a monthly basis are presented in table 6.1. The data for the three stock markets is pooled together and presents the mean value of the data series, its standard deviation and the minimum and maximum value. As expected the volatility measured by taking the logarithmic range between the daily high and low values ($VOL_{HL}$) is consistently higher on all of the three stock markets than the volatility measured as the standard deviation of the daily closing prices ($VOL_{SD}$), with only a few exceptions. This results in a substantially higher mean value of 30.2% versus 23.8%, respectively. Although the two different volatility measures have different characteristics, the patterns and monthly movements are very similar to each other, as presented in figure 6.1. The direction of the first differences is only in four of the twenty-five months analyzed different. As a result, the regression output for both measures is similar as well, but using both volatility measures as dependent variable is still valuable as it gives more insight into the sensitivity of the explanatory variables to the method used to estimate volatility.

Looking at the fraction of trading that can be attributed to HFTs on each of the three stock markets, it is noticeable that the fraction on the Copenhagen Stock Exchange is consequently lower than the fractions on the Stockholm Stock Exchange and the Helsinki Stock Exchange. The lowest monthly fraction of HFT during the time span is 1.98% and hence, is measured on the Copenhagen Stock Exchange. The highest participation on average is found on the Swedish Stock Exchange, on which also the highest fraction is measured; 18.86% on average in August 2011. Figure 6.1 demonstrates that the development of HFTs' fraction of the total market turnover follow a somewhat similar pattern as the monthly volatility, with the highest percentages being recorded in the second half of 2011 and a noticeable decline being experienced in the first two months of 2012.

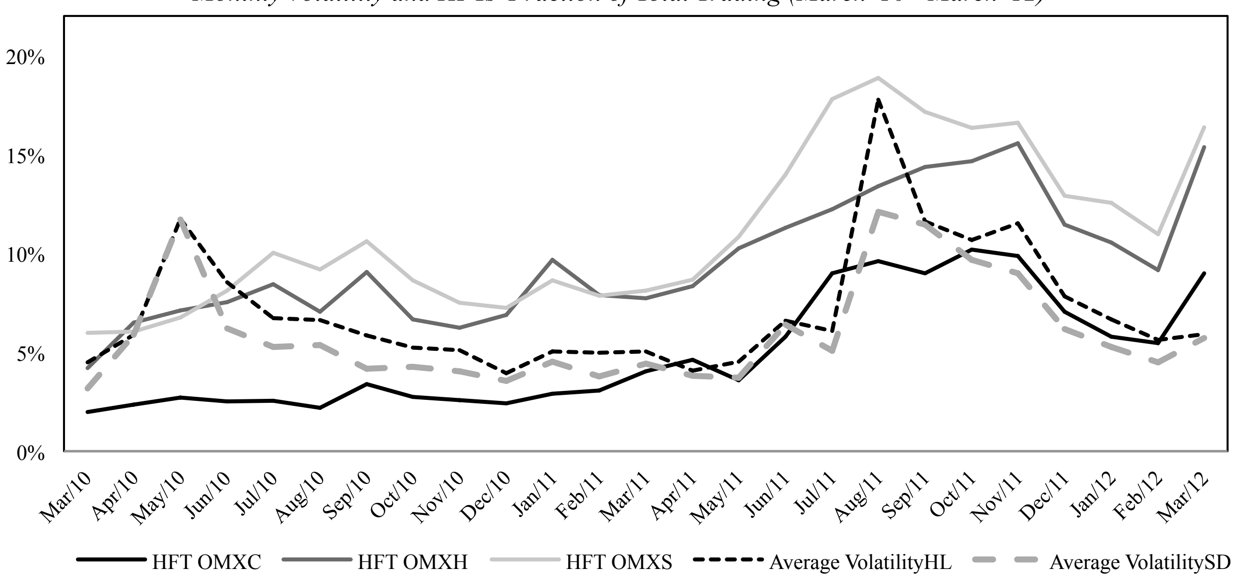
Table 6.1

| *Summary Statistics (Monthly Pooled Panel-Data)* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Name of variables | no. of Obs. | Cross Sections | Mean | Std. Deviation | Min. | Max. | ADF[a] statistic | Prob. |
| *Stock Market Volatility* | | | | | | | | |
| $VOL_{HL}$ (%) | 183 | 3 | 30.20 | 14.66 | 12.96 | 91.54 | 28.62 | 0.000 |
| $VOL_{SD}$ (%) | 183 | 3 | 23.84 | 11.92 | 9.22 | 75.09 | 25.03 | 0.000 |
| *Macroeconomic Policy Uncertainty* | | | | | | | | |
| Log of Money Supply (M2) | 219 | 3 | 13.22 | 1.24 | 11.24 | 14.61 | 11.85 | 0.065 |
| Exchange Rate Volatility (%) | 183 | 3 | 8.74 | 5.28 | 2.62 | 31.27 | 28.27 | 0.000 |
| Interest Rate Volatility (%) | 219 | 3 | 8.77 | 13.35 | 0.00 | 120.93 | 40.60 | 0.000 |
| *Business-Cycle Indicators* | | | | | | | | |
| Inflation Volatility (%) | 144 | 3 | 0.73 | 0.52 | 0.00 | 3.43 | 56.82 | 0.000 |
| Industrial Production Vol.(%) | 144 | 3 | 13.09 | 7.87 | 0.00 | 45.24 | 59.01 | 0.000 |
| Terms of Trade Volatility (%) | 144 | 3 | 2.90 | 1.56 | 0.00 | 7.09 | 61.87 | 0.000 |
| *Market Activity* | | | | | | | | |
| Log of Turnover | 183 | 3 | 21.92 | 1.34 | 19.67 | 24.14 | 17.29 | 0.001 |
| *HFTs' Activity* | | | | | | | | |
| HFTs' Fraction of Trading (%) | 75 | 3 | 8.58 | 4.26 | 1.98 | 18.86 | 12.51 | 0.052 |

[a] ADF-Fisher Chi Square panel unit root test. Null hypothesis assumes individual unit root process.

Figure 6.1

*Monthly Volatility and HFTs' Fraction of Total Trading (March '10 - March '12)*




### 6.1.1 Testing for Multicollinearity

The pair-wise correlation matrix for the employed variables is presented in Appendix I for each of the three stock exchanges. The matrix shows that, as expected, both used volatility measures are highly correlated with each other with the correlation being higher than 90% for all three stock exchanges. Further, of all the independent variables the volatility of the exchange rate and

HFTs' fraction of trading are on average closest related to the stock market volatility. In order to test the severity of multicollinearity among the explanatory variables the variance inflation factor (VIF) is estimated for all of the regressors. The conclusion can be drawn that there is no severe multicollinearity existent between the independent variables in the regressions for all three stock exchanges. The highest VIF score is 2.94 for the Stockholm Stock Exchange, 4.07 for the Copenhagen Stock Exchange and 3.57 for the Helsinki Stock Exchange, which is safely below the generally used critical VIF score of 5.

### *6.1.2 Testing for Stationarity*

The Augmented Dicked-Fuller (ADF) Fisher Chi-square panel unit root test is used to test the stationarity of the variables. The null-hypothesis, stating that the time-series is a random walk, can be rejected for all except two variables within a confidence level of 95% as shown in the last column of table 1. The test-statistic for the logarithm of the money supply has a probability of 0.065 and cannot be rejected as a result. The same is true for HFTs' fraction of trading. Individual ADF-tests for all three stock markets separately shows comparable results. Since both the logarithm of the money supply and the first difference of this variable have no significant influence on stock market volatility and there is not enough evidence to exclude non-stationarity, the variable is not included in the final regressions. Since HFTs' activity is measured as fraction of total trading activity, it will by definition have a value between 0 and 1and cannot drift away in the long-term. Further tests for stationarity, by using daily data, provide evidence with high significance that the variable is stationary. In addition, the null-hypothesis is rejected for all other variables. Hence, the fact that the null-hypothesis cannot be rejected for the pooled data with a confidence level of 95% is not assumed to give spurious regression outcomes.

## 6.2 Daily Summary Statistics

Table 6.2 presents the summary statistics for the variables used in the regressions with daily data. Besides the variable that proxies the fraction of the market turnover that can be attributed to HFTs, the natural logarithm of the total market turnover is additionally included in the regression model as explanatory variable. The conditional volatility as presented in the table is estimated by the EGARCH model, in which HFTs' fraction of trading and the logarithm of the market turnover are included directly in the variance equation as independent variables. The average annualized daily conditional volatility is close to the average annualized monthly unconditional volatility, but the standard deviation is substantially higher. Still, the overall pattern of the estimated daily stock market volatility is similar to the monthly volatility, which is based on two different measures. Figure 6.2 demonstrates that increased levels of volatility were experienced in mid-2010 and toward the end of 2011, with peaks of over fifty percent annualized daily conditional volatility. While the average conditional volatility on the Stockholm Stock Exchange and the Helsinki Stock Exchange is very similar with values of 24.1% and 24.7%, respectively, the average on the Copenhagen Stock Exchange is significantly lower with 19.3%.

The Stockholm Stock Exchange is the largest of the three stock markets when it comes to total capitalization and also has the highest daily market turnover, with an average of just over 14 billion Swedish krona from March 2010 to March 2012. It is also the exchange with the highest presence of HFTs, as shown by figure 6.3, and where the highest daily fraction of trading by HFTs is recorded (26,7% on August 26, 2011).

Table 6.2

*Summary Statistics (Daily Data)*

| Name of variables | no. of Obs. | Mean | Std. Deviation | Min. | Max. | ADF t-Statistic | Unit Root prob. |
|---|---|---|---|---|---|---|---|
| *Conditional Volatility[a] (%)* | | | | | | | |
| Stockholm Stock Exchange | 514 | 24.08 | 25.44 | 7.68 | 68.68 | -4.19 | 0.001 |
| Copenhagen Stock Exchange | 515 | 19.28 | 17.88 | 9.50 | 47.26 | -4.04 | 0.001 |
| Helsinki Stock Exchange | 512 | 24.72 | 21.93 | 11.11 | 50.19 | -3.00 | 0.036 |
| *Log of Market Turnover* | | | | | | | |
| Stockholm Stock Exchange | 551 | 23.33 | 0.29 | 21.66 | 24.36 | -13.50 | 0.000 |
| Copenhagen Stock Exchange | 548 | 21.68 | 0.33 | 20.15 | 23.74 | -6.13 | 0.000 |
| Helsinki Stock Exchange | 550 | 20.03 | 0.33 | 18.51 | 21.87 | -6.11 | 0.000 |
| *HFTs' Fraction of Trading (%)* | | | | | | | |
| Stockholm Stock Exchange | 508 | 10.82 | 4.47 | 2.39 | 26.66 | -4.00 | 0.010 |
| Copenhagen Stock Exchange | 503 | 4.88 | 3.20 | 0.54 | 15.59 | -4.03 | 0.008 |
| Helsinki Stock Exchange | 506 | 8.29 | 3.49 | 1.02 | 19.09 | -4.32 | 0.003 |

[a] Square root of annualized daily conditional variance, based on 260 trading days

Figure 6.2
*Annualized Conditional Daily Stock Market Volatility (March '10 - March '12)*

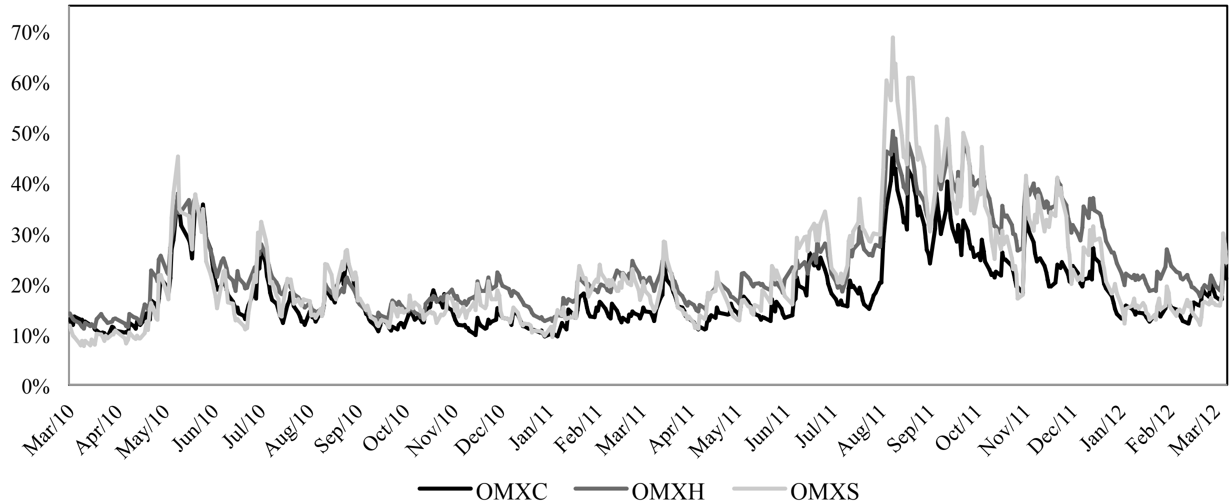
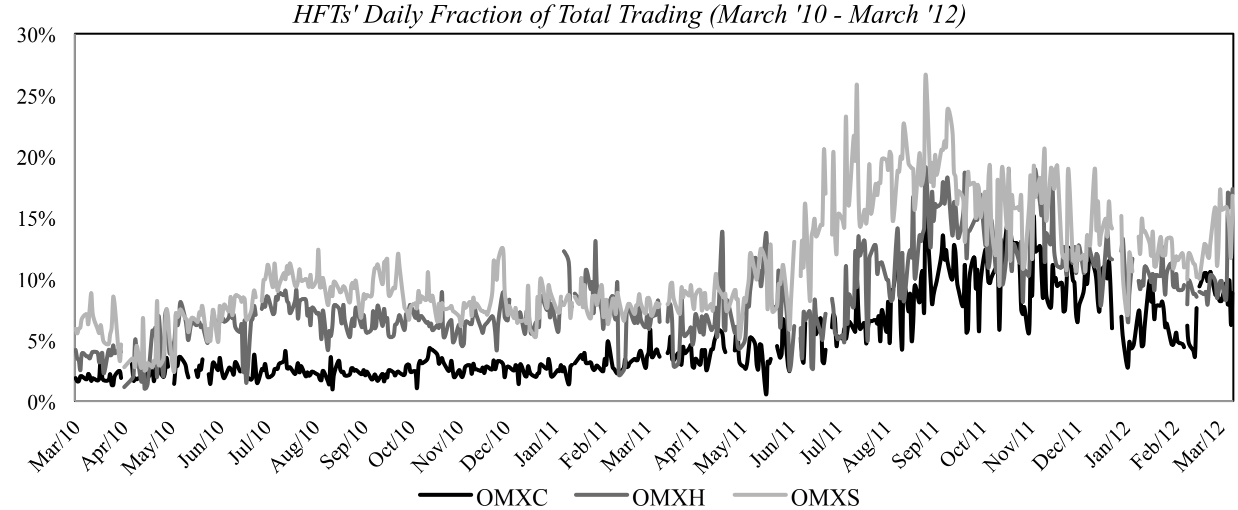



Figure 6.3
*HFTs' Daily Fraction of Total Trading (March '10 - March '12)*




### *6.2.1 Correlation, Multicollinearity and Stationarity*

Appendix II presents the pair-wise correlation matrix for the variables used in the daily analysis. In the analyzed period HFTs' fraction of trading is negatively correlated to the market turnover on all three stock exchanges and positively correlated with the conditional volatility. Just as for the variables used in the monthly analysis, multicollinearity of the variables is not an issue. All VIF scores are lower than 1.10, a result of the low coefficients of determination when regressing the logarithm of the market turnover against HFTs' fraction of the turnover. Stationarity is tested by using the Augmented Dickey-Fuller (ADF) unit root test and as the right column of table 6.2

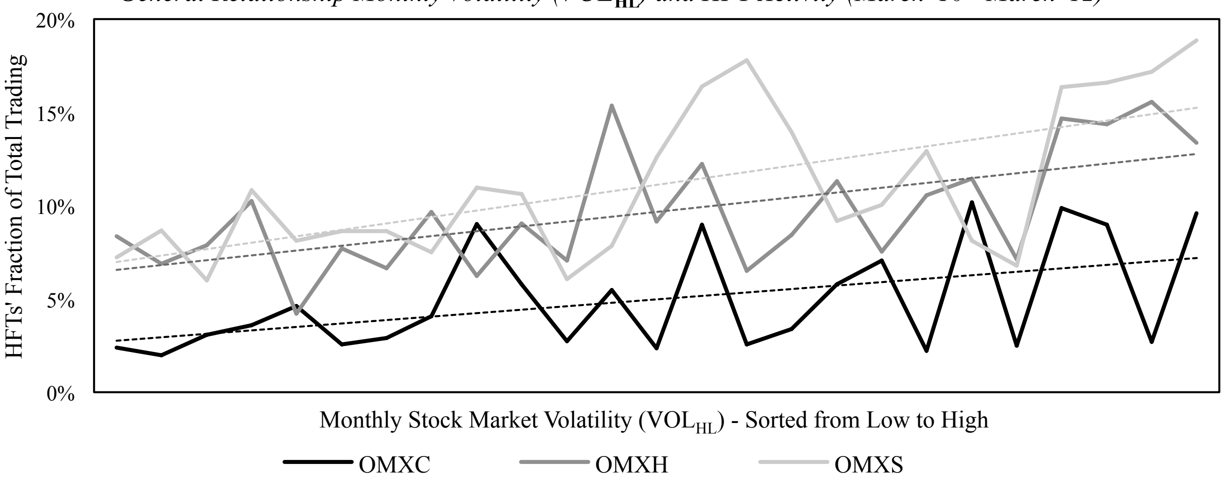
shows, the null-hypothesis, that implies that the time series has a unit root and is therefore non-stationary, can be rejected for all variables for a 5% significance level.

# 7 Empirical Results and Analysis

## 7.1 General Relationship between Monthly Stock Market Volatility and HFT Activity

As demonstrated in section 6.1, the development of monthly HFT activity and stock market volatility follow somewhat similar patterns during a large part of the investigated time period. In figure 7.1 HFTs' fraction of the total market turnover is plotted against the stock market volatility based on the high-low range ($VOL_{HL}$), which is sorted from low to high. The trend lines included in the graph all show an increasing trend, which confirms the positive correlation as presented in the pair-wise correlation matrix. Furthermore, the graph suggests that the level of HFT activity generally becomes more volatile toward higher levels of stock market volatility.

Figure 7.1
*General Relationship Monthly Volatility (**$VOL_{HL}$**) and HFT Activity (March '10 - March '12)*




## 7.2 Monthly HFT Activity and Stock Market Volatility

### *7.2.1 Macroeconomic Policy Uncertainty*

The statistical relationship between stock market volatility and the variables used to control for the effect of macroeconomic policy uncertainty is reported in table 7.1. The first column reports the regression with the natural logarithm of the money supply as the only regressor. For both volatility measures the money supply is negatively correlated to stock market volatility, but due to a relatively high standard error the variable is insignificant in both cases. In contrast, both the volatility of the exchange rate and the volatility of the interest rate, reported in column 2 and 3, respectively, are positively correlated to the stock market volatility at the highest significance level of 1%. The variables remain significant when including them both as explanatory variables in the regression as reported in column 4 and together have a coefficient of determination of 0.25 for both volatility measures. The logarithm of the money supply is due to its unit root, as discussed in section 6.1.2, and its consistent insignificance dropped from the model in subsequent regressions. Including the variable together with the volatility of the exchange rate and the volatility of the interest rate in the model appears to decrease the adjusted coefficient of determination of the regression and may bias the inferences.

Table 7.1 *(a)*
*Monthly Stock Market Volatility and Macroeconomic Policy Uncertainty*
Dependent Variable: Volatility based on log-range of daily high-low ($\boldsymbol{VOL}_{\mathbf{HL}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Log of Money Supply (M2) | -0.008 (0.009) | | | |
| Exchange Rate Volatility (%) | | 1.36 (0.18)*** | | 1.24 (0.19)*** |
| Interest Rate Volatility (%) | | | 0.29 (0.07)*** | 0.12 (0.07)* |
| Constant | 0.40 (0.12)*** | 0.18 (0.02)*** | 0.27 (0.01)*** | 0.18 (0.02)*** |
| No. of Observations | 183 | 183 | 183 | 183 |
| Adj. R-squared | -0.008 | 0.24 | 0.08 | 0.25 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7.1 *(b)*
*Monthly Stock Market Volatility and Macroeconomic Policy Uncertainty*
Dependent Variable: Volatility based on standard deviation of daily returns ($\boldsymbol{VOL}_{\mathbf{SD}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Log of Money Supply (M2) | -0.009 (0.007) | | | |
| Exchange Rate Volatility (%) | | 1.12 (0.15)*** | | 1.01 (0.15)*** |
| Interest Rate Volatility (%) | | | 0.24 (0.06)*** | 0.10 (0.06)* |
| Constant | 0.36 (0.10)*** | 0.14 (0.15)*** | 0.21 (0.01)*** | 0.14 (0.01)*** |
| No. of Observations | 183 | 183 | 183 | 183 |
| Adj. R-squared | 0.003 | 0.24 | 0.08 | 0.25 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

### *7.2.2 Business-Cycle Indicators*

The second set of variables tested for their interaction with the volatility of the stock market are the business-cycle indicators; inflation volatility, industrial production volatility and terms of trade volatility. Testing them individually as explanatory variables to both volatility measures results in insignificant coefficients except for the volatility of the inflation, which is marginally significant with the volatility based on the standard deviation of the returns as dependent variable. The explanatory power of all three variables individually is low, as demonstrated by the bottom rows of table 7.2 (*a* and *b*). Including the three variables together with the variables that were proven to be significant in the previous set of regressions provides only one marginally significant relationship to the stock market volatility when it comes to the business-cycle indicators; industrial production volatility is negatively related to the volatility based on the high-low range at a 10% significance level. As reported in column 4 of the tables, the coefficients of the volatility of the inflation are highly insignificant, show different signs for both volatility measures and do not add any explanatory value to the model. The terms of trade index also does not provide any explanatory value to the model when adjusting for the degrees of freedom as the coefficients are consistently insignificant. Hence, both variables are dropped from the model. The volatility of the industrial production index, in all four the regression negatively correlated to the stock market volatility, is due to its marginal significance remained in the model in subsequent regressions.

Table 7.2 *(a)*
*Monthly Stock Market Volatility and Business-Cycle Indicators*
Dependent Variable: Volatility based on log-range of daily high-low (***VOL***$_{\mathbf{HL}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Inflation Volatility (%) | 3.95 (2.52) | | | -0.34 (2.46) |
| Industrial Production Volatility (%) | | -0.19 (0.17) | | -0.26 (0.15)* |
| Terms of Trade Volatility (%) | | | -0.51 (0.85) | 0.48 (0.75) |
| Exchange Rate Volatility (%) | | | | 1.38 (0.23)*** |
| Interest Rate Volatility (%) | | | | 0.11 (0.08) |
| Constant | 0.28 (0.02)*** | 0.33 (0.03)*** | 0.32 (0.03)*** | 0.18 (0.04)*** |
| No. of Observations | 144 | 144 | 144 | 144 |
| Adj. R-squared | 0.01 | 0.01 | 0.000 | 0.25 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7.2 *(b)*
*Monthly Stock Market Volatility and Business-Cycle Indicators*
Dependent Variable: Volatility based on standard deviation of daily returns (***VOL***$_{\mathbf{SD}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Inflation Volatility (%) | 3.79 (2.05)* | | | 0.33 (2.01) |
| Industrial Production Volatility (%) | | -0.12 (0.14) | | -0.19 (0.12) |
| Terms of Trade Volatility (%) | | | -0.09 (0.69) | 0.72 (0.62) |
| Exchange Rate Volatility (%) | | | | 1.11 (0.19)*** |
| Interest Rate Volatility (%) | | | | 0.09 (0.06) |
| Constant | 0.22 (0.02)*** | 0.26 (0.02)*** | 0.25 (0.02)*** | 0.13 (0.03)*** |
| No. of Observations | 144 | 144 | 144 | 144 |
| Adj. R-squared | 0.02 | 0.01 | 0.000 | 0.25 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

### *7.2.3 Market Activity and HFT Activity*

The relationship between the natural logarithm of the market turnover and volatility is tested as a last step in building the final regression model. Whereas the coefficients, reported in column 1 of table 7.3, are insignificant when the variable is used as the only regressor, the coefficients are significant at the highest level when they are added to the final model from the last section, as reported in column 3. Adding the variable to the model increases the explanatory power of the model significantly, indicated by the increase of the adjusted $R^2$ from 0.25 to 0.32 and 0.33 for $VOL_{\mathrm{HL}}$ and $VOL_{\mathrm{SD}}$, respectively. As a result of these findings, the variable is part of the final model. Hence, the final model includes in addition to HFTs' fraction of trading four explanatory variables; interest rate volatility, exchange rate volatility, industrial production volatility and the logarithm of the total market turnover.

With the final regression model in place, the relationship between HFT activity and stock market volatility can be tested. First, HFT activity is tested as only explanatory variable for stock market volatility. Regressing HFTs' fraction of the market turnover as only regressor against the two volatility measures results in positive coefficients, both significant at the highest level. The coefficients, reported in column 2, are only marginally different from each other for both volatility measures. The values of 1.49 and 1.24 for $VOL_{\mathrm{HL}}$ and $VOL_{\mathrm{SD}}$, respectively, imply that during the time period under investigation, annualized stock market volatility has on average been more than 1% higher for every percentage increase in HFTs' fraction of trading. Moreover, the variable on its own has almost as much explanatory power as the four control variables combined, as demonstrated by the coefficient of determination of 0.29 for both volatility estimation methods. Adding the four control variables to the regression increases the adjusted $R^2$ further to 0.35, as presented in column 4 of table 7.3. The coefficients of HFTs' fraction of trading remain significant at the highest level in both regressions, although they decrease respectively from 1.49 to 1.26 and from 1.24 to 0.94.

Overall, the regressions provide strong evidence for a positive interaction between stock market volatility and HFTs' trading activity during the observed 25 months on the three stock exchanges combined. Moreover, also after an additional test, conducted by augmenting the model with an additional variable that captures a potential linear time trend and a lagged dependent variable that controls for potential remaining serial correlation in volatility, the relationship between HFT activity and volatility is highly significant. The highly insignificant coefficients of the two additional variables further confirm the reliability of the model and minimize the possibility of a spurious relationship.

Table 7.3 *(a)*
*Monthly Stock Market Volatility, Market Activity and HFT Activity*
Dependent Variable: Volatility based on log-range of daily high-low ($\boldsymbol{VOL}_{\mathbf{HL}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Log of Turnover | 0.002 (0.008) | | -0.04 (0.01)*** | -0.02 (0.01)* |
| **HFTs' Fraction of Trading (%)** | | **1.49 (0.27)*** ** | | **1.26 (0.29)*** ** |
| Industrial Production Volatility (%) | | | -0.25 (0.14)* | -0.22 (0.13) |
| Exchange Rate Volatility (%) | | | 1.81 (0.25)*** | 0.81 (0.37)** |
| Interest Rate Volatility (%) | | | 0.11 (0.07) | 0.05 (0.21) |
| Constant | 0.26 (0.18) | 0.12 (0.03)*** | 0.92 (0.20)*** | 0.54 (0.22)** |
| No. of Observations | 183 | 75 | 144 | 75 |
| Adj. R-squared | 0.000 | 0.29 | 0.32 | 0.35 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

Table 7.3 *(b)*
*Monthly Stock Market Volatility, Market Activity and HFT Activity*
Dependent Variable: Volatility based on standard deviation of daily returns ($\boldsymbol{VOL}_{\mathbf{SD}}$)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Log of Turnover | -0.002 (0.007) | | -0.03 (0.01)*** | -0.02 (0.01)*** |
| **HFTs' Fraction of Trading (%)** | | **1.24 (0.22)*** ** | | **0.94 (0.23)*** ** |
| Industrial Production Volatility (%) | | | -0.17 (0.11) | -0.14 (0.11) |
| Exchange Rate Volatility (%) | | | 1.50 (0.20)*** | 1.01 (0.30)*** |
| Interest Rate Volatility (%) | | | 0.08 (0.06) | -0.09 (0.17) |
| Constant | 0.29 (0.15) | 0.10 (0.02)*** | 0.83 (0.16)* | 0.59 (0.17)*** |
| No. of Observations | 183 | 75 | 144 | 75 |
| Adj. R-squared | 0.001 | 0.29 | 0.33 | 0.40 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

### *7.2.4 Individual Regressions for the Stock Exchanges*

In addition to the pooled panel regressions for the three Nordic stock exchanges combined, the same procedure is conducted for each of the exchanges individually. The sequential estimation technique, i.e. adding additional explanatory variables step by step and retain only the ones found significant at the 10% level, is repeated in order to get the most reliable regression outcomes without biased inferences. The outcomes of the final regression models are reported in appendix III (*a* to *c*). A statistically significant relationship with stock market volatility for all three stock markets is found for the volatility of the exchange rate and the logarithm of the market turnover. In addition, in the analysis of the Stockholm Stock Exchange the inflation volatility and the interest rate volatility are found to be significantly related to stock market volatility and the same is true for the terms of trade volatility and the interest rate volatility for the Copenhagen Stock Exchange. Hence, these variables are included in the final regression model for the respective stock exchange.

On all three of the Nordic stock exchanges the activity of HFTs is found to be positively related to stock market volatility, both when regressed as only explanatory variable and after controlling for other influences by adding the set of control variables. Moreover, all coefficients are statistically significant at the 10% level and for both the Helsinki Stock Exchange and the Stockholm Stock Exchange all the coefficients are even significantly different from zero at the 1% level. The adjusted coefficients of determination for the full models range from a minimum of 0.37 on the Helsinki Stock Exchange to 0.65 on the Stockholm Stock Exchange, meaning the employed regressors have fairly strong explanatory power with respect to stock market volatility. The weakest evidence for a statistically significant relationship between HFT activity and stock market volatility is found for the Copenhagen Stock Exchange, which is also the market with on average the lowest participation level of HFTs. The substantially lower fraction of trades that can be contributed to HFTs on the Copenhagen Stock Exchange and the lowest standard deviation of the average monthly fraction could be highlighted as an explanation for the somewhat weaker relationship with stock market volatility, although there is no statistical evidence to support this.

### 7.3 Testing for Normality, Autocorrelation and Heteroscedasticity

The tables in appendix III also include the Jarque-Bera statistics to test the normality assumption. The normality assumption is violated in only one case when using a confidence level of 95%. The final regression for the Helsinki Stock Exchange with $VOL_{\mathrm{HL}}$ as the dependent variable has a Jarque-Bera Statistic of 6.59, or equivalently a p-value of 0.04. This means that the null hypothesis, which implies the residuals are normally distributed, has to be rejected for this regression. However, given that both the regression for the Helsinki Stock Exchange with $VOL_{\mathrm{SD}}$ as the dependent variable and all the final regressions for the two other stock exchanges have low Jarque-Bera statistics and therefore do not violate the normality assumption, non-normality of the residuals is not considered as an issue and is not expected to result in flawed outcomes.

The Breusch-Godfrey test is used to test for autocorrelation in the residuals. The null hypothesis states that the residuals are not auto-correlated and is not rejected for any of the final regression models. The highest F-statistic is found for the residuals of the Stockholm Stock Exchange with $VOL_{\mathrm{HL}}$ as the dependent variable, but the score of 1.60 is equivalent to a probability of 0.23 and hence, the null-hypothesis is not rejected.

To test the underlying assumption that the variance of the errors is constant over time, the autoregressive conditional heteroscedasticity (ARCH) test is conducted on the residuals of the final regression models. The highest F-statistic when using 1 lag is with a value of 3.26 found for the residuals of the Stockholm Stock Exchange with $VOL_{\mathrm{HL}}$ as the dependent variable. Using a confidence level of 95%, the according probability of 0.08 means the null hypothesis, which implies the residuals exhibit no conditional heteroscedasticity, is not rejected for any of the final regression models.

### 7.4 Daily HFT Activity and Conditional Stock Market Volatility

The output of the regressions that test the relationship between daily conditional stock market volatility and HFT activity is presented in table 7.4. The uneven columns (1, 3 and 5) report the regression results in which HFT activity is used as only additional explanatory variable in the variance equation for the Stockholm Stock Exchange, Copenhagen Stock Exchange and Helsinki Stock Exchange, respectively. On both the Stockholm Stock Exchange and Copenhagen Stock Exchange the activity of HFTs is found to be positively related to the conditional stock market volatility with statistical significance at the highest level. For the Helsinki Stock Exchange the level of HFT activity is also positively related to the conditional volatility, but the coefficient is not statistically significant. However, after controlling for the total market turnover the relationship between HFT activity and conditional volatility is significant positive for all three stock exchanges. The natural logarithm of the market turnover is also positively related with the conditional variance on all three exchanges, although neither of the coefficients are statistically significant at the 10% level.

Looking at the other coefficients that determine the conditional variance in the equation, the fact that parameter $\alpha$ has a value of close to 1 in all six regressions demonstrates the persistence of daily volatility. Furthermore, the significant negative values of all $\beta$ parameters demonstrate the existence of asymmetry in volatility. More specifically, they provide evidence that positive shocks with respect to the market return generate less volatility then negative shocks.

Table 7.4

*Conditional Daily Stock Market Volatility, Market Activity and HFT Activity*

$$r_t = a + b\, r_{t-1} + \varepsilon_t \text{ where } E_t(\varepsilon_t) = 0 \text{ and } E_{t-1}(\varepsilon_t^2) = \sigma_t^2$$

$$\ln \sigma_t^2 = \omega + \alpha_t \ln(\sigma_{t-1}^2) + \beta \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \gamma \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + \theta\, Turnover_t + \varphi\, HFT_t$$

| | OMXS | | OMXC | | OMXH | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| a | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.001) |
| b | 0.020 | 0.020 | -0.011 | -0.010 | 0.057 | 0.055 |
| | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) | (0.049) |
| ω | -0.881 | -2.564 | -0.854 | -1.722 | -0.507 | -1.637 |
| | (0.189)*** | (1.113)** | (0.247)*** | (1.172) | (0.209)** | (0.909)* |
| α | 0.922 | 0.921 | 0.928 | 0.926 | 0.956 | 0.946 |
| | (0.016)*** | (0.016)*** | (0.024)*** | (0.025)*** | (0.020)*** | (0.021)*** |
| β | -0.251 | -0.232 | -0.151 | -0.145 | -0.121 | -0.118 |
| | (0.036)*** | (0.037)*** | (0.036)*** | (0.038)*** | (0.027)*** | (0.029)*** |
| γ | 0.118 | 0.096 | 0.194 | 0.190 | 0.109 | 0.098 |
| | (0.044)*** | (0.050)* | (0.055)*** | (0.058)*** | (0.040)*** | (0.049)** |
| θ | | 0.072 | | 0.038 | | 0.051 |
| | | (0.047) | | (0.052) | | (0.042) |
| **φ** | **0.920** | **0.954** | **1.020** | **1.191** | **0.540** | **0.867** |
| | **(0.341)*** ** | **(0.334)*** ** | **(0.461)*** ** | **(0.506)** ** | **(0.428)** | **(0.493)* ** |
| No. of obs. | 508 | 508 | 503 | 503 | 506 | 506 |
| Jarque-Bera[a] | 7.53 [0.023][b] | 4.93 [0.085] | 0.11 [0.947] | 0.20 [0.903] | 4.05 [0.132] | 2.52 [0.283] |
| ARCH F-stat. | 1.69 [0.195] | 1.46 [0.228] | 0.70 [0.405] | 0.63 [0.426] | 1.63 [0.202] | 1.92 [0.167] |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.
[a] Probability is denoted within [..]. Null-hypothesis implies that the underlying assumption is not violated.
[b] Null-hypothesis that assumes the residuals are normally distributed is rejected only for this regression within a 95% confidence level.

## 7.5 Testing for Normality and Autocorrelation

The two bottom rows of table 7.4 contain the test statistics for the normality test and the autocorrelation test. Just as for the monthly analysis the Jarque-Bera test is used to test the normality of the residuals. The null-hypothesis, implying that the residuals are normally distributed and therefore the underlying assumption of normality is not violated, is rejected in one regression within a confidence level of 95%. The residuals of the regression for the Stockholm Stock Exchange, with HFTs' fraction of trading as the only additional explanatory variable in the variance equation, have a test statistic of 7.53. However, after controlling for the total market turnover there is not enough evidence anymore to reject the null-hypothesis and therefore the residuals are assumed to be normally distributed.

In order to test for autocorrelation in the residuals the ARCH F-statistic is estimated for all regressions. Since the variance equation of the EGARCH model is an autoregressive-moving average (ARMA) model of the residuals, the model usually filters out any autocorrelation of the residuals. The highest estimated statistic is 1.92, based on the residuals of the regression for the Helsinki Stock Exchange. Hence, the null-hypothesis that states the residuals are not auto-correlated is not rejected in any of the regressions, as expected by the authors.

## 7.6 Testing the Direction of the Relationship

After demonstrating a statistically significant positive contemporaneous relationship between HFT and stock market volatility, both on a daily and a monthly basis, it is interesting to get more insight in the dynamic relationship between both. With the current findings that HFT activity is typically higher when volatility levels are higher it is not possible to draw any conclusions about the direction of causality, i.e. whether higher HFT activity increases volatility or higher volatility increases HFT activity. Moreover, the relationship can be bidirectional, meaning that higher volatility increases the incentive of HFTs to trade and volatility as a result further increases because of the increased activity of HFTs. Although the direction of the relationship is difficult to determine, the contemporaneous relationship can be further investigated to get more understanding of HFTs behavior under different volatility conditions. In this section two procedures are followed to gain a better understanding of the interdependence between both processes. As a first step, HFTs participation level is analyzed for different levels of volatility and during days with negative and positive stock market returns and then the Granger causality test is implemented to statistically test the dynamic relationship between HFT activity and volatility.

### *7.6.1 HFTs' Activity in Different Volatility Environments*

One of the main concerns regarding HFT relates to the uncertainty about HFTs' behavior during adverse market conditions, as discussed in section 2.2. Due to the noncommittal nature of their role as passive market maker, liquidity could vanish and volatility aggravate during times of market stress, as a result of HFTs that may temporary withdraw themselves from the market. However, since negative shocks in the market are often the result of news releases, HFTs that have faster access to market data and lower response times can have increased incentives to trade during higher levels of volatility.

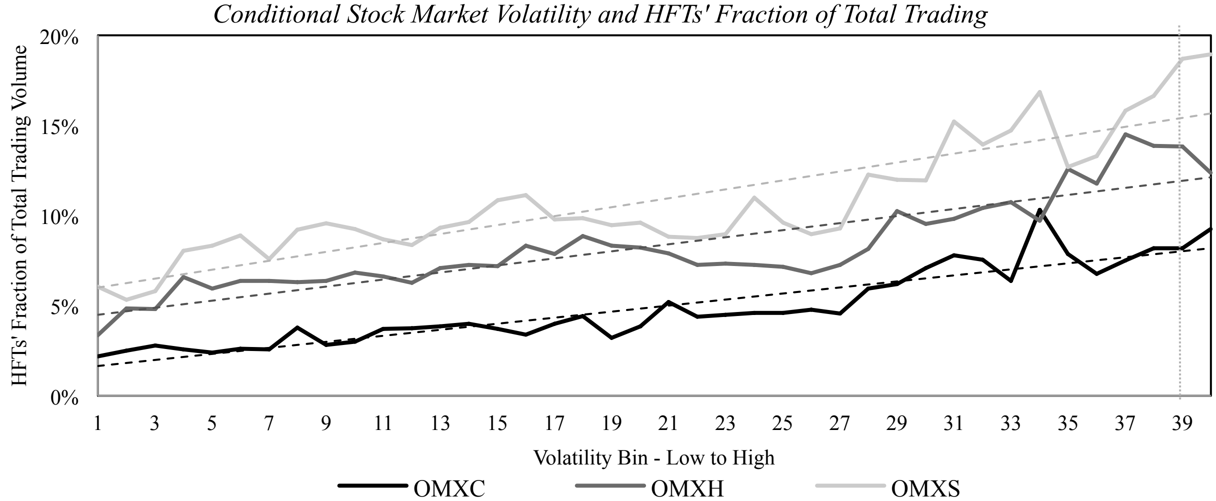
In order to analyze the behavior of HFTs during different levels of volatility, the daily volatility is sorted from low to high and clustered in 40 groups. Sorting the daily volatility levels from low to high and bundle them in 40 groups is an efficient way to limit noise whilst still retain an appropriate number of observations to determine the general relationship. As pointed out in section 3.1.3, Brogaard (2010) found that HFTs' participation does not substantially increase or decrease for different volatility levels, although volatility demanding activity generally increases and volatility supplying activity generally decreases for higher levels of volatility. However, further research based on intraday time intervals, presented in a spin off of the initial paper (Brogaard, 2011a), points out that HFTs' activity varies significantly as the level of volatility changes for intraday time intervals. For a majority of the time intervals, ranging from 10 seconds to 210 minutes, Brogaard finds that the activity of HFTs decreases under the most volatile conditions, although the reduced activity is rather small and not found for all time intervals. Given these findings and the concerns that HFTs may reduce their trading activity during extreme market conditions, it is of interest to analyze whether the activity of HFTs on the Nordic stock exchanges deviates from their normal behavior on the most volatile days.

Figure 7.2 demonstrates the activity of HFTs as function of the level of the conditional daily volatility, clustered together from low to high in 40 groups. The graph does not show any major breaks in the generally positive trends. Except on the Helsinki Stock Exchange the participation of HFTs did not decrease on the 2.5% most volatile days and an additional analysis for the 1% most volatile days leads to the same findings. Conducting the same analysis for trading days with positive returns and days with negative returns separately, the results of which are presented in appendix IV*(a)* and IV*(b)*, respectively, also leads to the same conclusion. The figures do in addition not demonstrate material differences in HFT activity between trading days with positive and negative returns. As a last test the procedure is repeated for the volatility based on the logarithmic daily high-low range ($VOL_{HL}$). The figure, presented in appendix IV*(c)*, generally shows the same pattern as for the conditional volatility, with the only noticeable difference being the fact that HFT activity decreases both on the Helsinki Stock Exchange and on the Copenhagen Stock Exchange on the 2.5% most volatile trading days, although the declines are rather small and the activity of HFTs is still above average on these days.

Altogether, the observations in this section do not lead to additional insights with respect to the previously demonstrated generally positive relationship between HFTs' participation level and stock market volatility. Moreover, the study does not find evident signs of decreased HFT activity in volatile environments.

Figure 7.2

*Conditional Stock Market Volatility and HFTs' Fraction of Total Trading*




### *7.6.2 Granger Causality Test*

The Granger causality test is implemented to statistically investigate the dynamic relationship between HFT activity and volatility. Even though the test cannot determine whether HFT increases volatility or volatility increases HFT activity, it demonstrates whether an increase in one of the variables is preceded by an increase in the other variable; a necessary condition for a causal relationship between two variables. The results of the test between HFT activity and conditional stock market volatility are reported in table 7.5. On both the Helsinki Stock Exchange and the Stockholm Stock Exchange all test statistics are significant for at least the 10% level, meaning there is strong evidence for bidirectional Granger-causality. On the Copenhagen Stock Exchange the relationship is weaker and there is significant support for Granger causality in only half of the cases.

Table 7.5

*Granger Causality Test (Wald Test) for Conditional Daily Volatility and HFTs' Fraction of Trading*

| | **OMXS** | | **OMXC** | | **OMXH** | |
|---|---|---|---|---|---|---|
| | F-Stat. | prob. | F-Stat. | prob. | F-Stat. | prob. |
| *1lag* | | | | | | |
| HFT does not Granger Cause Volatility | 22.50*** | 0.000 | 2.99* | 0.085 | 11.90*** | 0.000 |
| Volatility does not Granger Cause HFT | 24.72*** | 0.000 | 5.53** | 0.019 | 34.60*** | 0.000 |
| *2 lags* | | | | | | |
| HFT does not Granger Cause Volatility | 13.20*** | 0.000 | 2.02 | 0.133 | 8.86*** | 0.000 |
| Volatility does not Granger Cause HFT | 3.64** | 0.027 | 1.56 | 0.211 | 8.49*** | 0.000 |
| *3 lags* | | | | | | |
| HFT does not Granger Cause Volatility | 9.47*** | 0.000 | 2.58* | 0.053 | 7.52*** | 0.000 |
| Volatility does not Granger Cause HFT | 2.31* | 0.075 | 1.29 | 0.276 | 3.44** | 0.017 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

The Granger causality test is also conducted for the unconditional volatility measure, $VOL_{HL}$. The test results, reported in table 7.6, suggest strong evidence for HFT Granger causing volatility, demonstrated by the significant test results for all three exchanges up to three lagged variables. The results for the Granger causality test in the other direction, i.e. increased volatility being followed by increased HFT activity, are more ambiguous. Only for the Helsinki Stock Exchange and the Stockholm Stock Exchange there is statistical evidence for bidirectional Granger-causality between the measured unconditional volatility and the activity of HFTs.

Table 7.6

*Granger Causality Test for Daily High-Low Volatility (**$VOL_{HL}$**) and HFTs' Fraction of Trading*

| | **OMXS** | | **OMXC** | | **OMXH** | |
|---|---|---|---|---|---|---|
| | F-Stat. | prob. | F-Stat. | prob. | F-Stat. | prob. |
| *1lag* | | | | | | |
| HFT does not Granger Cause Volatility | 35.71*** | 0.000 | 13.08*** | 0.000 | 18.24*** | 0.000 |
| $VOL_{HL}$ does not Granger Cause HFT | 15.17*** | 0.000 | 0.79 | 0.373 | 15.50*** | 0.000 |
| *2 lags* | | | | | | |
| HFT does not Granger Cause Volatility | 9.35*** | 0.000 | 5.14*** | 0.006 | 5.66*** | 0.004 |
| $VOL_{HL}$ does not Granger Cause HFT | 3.60** | 0.028 | 0.34 | 0.709 | 6.13*** | 0.002 |
| *3 lags* | | | | | | |
| HFT does not Granger Cause Volatility | 6.58*** | 0.000 | 2.49* | 0.060 | 2.59* | 0.052 |
| $VOL_{HL}$ does not Granger Cause HFT | 1.97 | 0.117 | 0.65 | 0.583 | 33.97*** | 0.008 |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

# 8 Conclusion and Discussion

Although HFT is an umbrella term for various trading strategies with each a different impact on market quality parameters, the purpose of this paper has been to explore the contemporaneous and dynamic relationship between the overall trading behavior of HFTs and the volatility of the Nordic stock markets. The empirical investigation is based on a unique dataset that currently provides, to the authors' knowledge, the best available proxy for HFT activity. The dataset identifies HFT's fraction of the total trading turnover on three of the Nordic stock markets for the period from March 2010 to March 2012, both for a daily and a monthly frequency. The dataset demonstrates that, despite the fact that the fraction of the market turnover that can be contributed to HFTs has on average increased during the investigated period, the activity of HFTs appears to vary substantially from day-to-day and month-to-month.

The analysis based on monthly data provides statistically significant evidence for a positive contemporaneous relationship between HFT and volatility on all three Nordic stock markets under investigation, both when using the activity of HFTs as only explanatory factor for stock market volatility and after controlling for the effect of the total market turnover and a set of macroeconomic variables that appeared to be related to market volatility. The analysis based on daily data, where the activity of HFTs is directly included in the conditional variance equation of the EGARCH model and which controls for the total market turnover and persistence of daily volatility, also finds a statistically significant and fairly strong positive relationship between HFT and volatility on all three stock markets. The results are surprisingly strong when comparing them to the findings of Brogaard (2010), who found only marginal variation in aggregate daily HFT activity for different levels of daily stock market volatility on the US market.

The findings are also interesting in the light of previous findings regarding algorithmic trading in general. Most research conducted on algorithmic trading does not find an evident positive contemporaneous and causal relationship with stock market volatility and hence, generally suggests that an increased fraction of algorithmic trading is not associated with higher levels of volatility. The strong interaction between HFT and volatility found in this paper accentuates the importance to analyze HFTs' impact on market quality parameters separately from algorithmic trading, as it has different characteristics.

One of the primary concerns regarding HFT, the suggestion that HFTs decrease their trading activity or completely withdraw themselves from the market in highly volatile environments, does not appear from the analysis in this paper. The participation level of HFTs on the most volatile days is not materially different from the somewhat less volatile days. However, as the dataset does not distinguish between supplying and demanding liquidity, the suggestion of Kirilenko et al. (2011) that HFTs may rebalance their positions during volatile environments and thereby compete for liquidity with other market participants, can not be invalidated. Shifting from liquidity supplying activities to liquidity demanding activities during times of market stress by HFT firms can result in vanishing liquidity and exacerbate price volatility, but a more specific dataset that distinguishes between liquidity supplying and demanding is needed to get a better understanding of HFTs' trading behavior in adverse market conditions.

Unlike the contemporaneous relationship between HFT and stock market volatility, the direction of the relationship is difficult to determine. The Granger-causality test points out that on all three exchanges a trading day with increased volatility is preceded by an increased fraction of HFT on the day before, i.e. HFT Granger causes volatility, but this does not imply causality in the more common sense. As the results in this paper do not address endogeneity between stock market volatility and HFT activity, there is no statistical evidence to determine the direction of the bias. However, the findings in this paper give good reason to suggest that the existence of trading opportunities for HFT firms is strongly positively correlated with the volatility of prices. To get a better understanding of the possible relationship in the other direction, i.e. HFT contributing to stock market volatility, further research needs to be done. With the findings in this paper, both the possibility that HFT contributes to volatility and the possibility that HFT dampens volatility can not be excluded, although the theoretical review in this paper has pointed out that the dynamic relationship may be highly dependent on the market circumstances.

To conclude, the current findings regarding HFT do not provide unequivocal evidence for a need to curb HFTs trading behavior. Further research needs to reveal if imposing limitations on HFTs is necessary and can be justified. Research focusing on intraday frequencies and stock specific data can provide valuable insight in the behavior of HFTs under different circumstances and also provides more possibilities to empirically investigate causality, for instance by analyzing situations in which there are exogenous shocks to volatility or HFT activity. Altogether, the empirical analysis of this paper provides a step toward a better understanding of the phenomenon HFT, but there is a lot more to discover in this to a large extent unexplored area of research.

# References


**Books**

Aldridge, I, 2012, *High Frequency Trading - A Practical Guide to Algorithmic Strategies and Trading Systems,* John Wiley & Sons: Hoboken, New Jersey

Alexander, C., 2009, *Practical Financial Econometrics,* John Wiley & Sons: Hoboken, New Jersey

Campbell, J. Y., Lo, A. W., MacKinlay, C. A., 2010, *The Econometrics of Financial Markets,* Princeton University Press: Princeton, New Jersey

Harris, L., 2003, *Trading and Exchanges: Market Microstructure for Practitioners*, Oxford University Press: Oxford

Kalotychou, E., Staikouras, S. K., 2009, *Stock Market Volatility,* Chapman & Hall/ CRC Finance: Boca Raton, FL

**Articles and Working Papers**

Alizadeh, S., Brandt, M. W., Diebold, F. X., 2002, Range-Based Estimation of Stochastic Volatility Models, *Journal of Finance, 7(3): 1047-1090*

Andersen, T.G., Bollerslev, T., 1998, Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts, *International Economic Review, 39: 885-905*

Balaban, E., Bayar, A., Faff, R W., 2006, Forecasting Stock Market Volatility: Further International Evidence, *The European Journal of Finance, 12(2): 171-188*

Bertsimas, D., Andrew W., Lo, 1998, Optimal Control of Execution Costs, *Journal of Financial Markets, 1: 1–50*

Blanchard, O., J., 1981, Output, the Stock Market and Interest Rates, *The American Economic review, 1: 132-143*

Blume, L., Easley, D., O'Hara, M., 1994, Market Statistics and Technical Analysis: The Role of Volume, *Journal of Finance, 49: 153-183*

Bollerslev, T., 1986, Generalized Autoregressive Conditional Heteroskedasticity, *Journal of Econometrics, 31: 307-327*

Bollerslev, T., M. Gibson and H. Zhou, 2004, *Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option Implied and Realized Volatilities*, Federal Reserve Board WP 2004-56

Brandt, M.W., Kang, Q., 2004, On the Relationship between the Conditional Mean and Volatility of Stock Returns: a Latent VAR Approach, *Journal of Financial Economics, 72: 217-257*

Brogaard, J., 2010, *High Frequency Trading and its Impact on Market Quality*, Northwestern Univeristy, Working Paper

Brogaard, J., 2011a, *High Frequency Trading and Volatility*, University of Washington, Working Paper

Brogaard, J., 2011b, *High Frequency Trading and Market Quality*, University of Washington, Working Paper

Brogaard, J., 2011c, *The Activity of High Frequency Traders,* University of Washington, Working Paper

Canina, L., Figlewski, S., 1993, The Informational Content of Implied Volatility, *Review of Financial Studies*, *6: 659-681*

Castura, J., Litzenberger, R., Gorelick, R., Dwivedi, Y., 2010, *Market Efficiency and Microstructure Evolution in U.S. Equity Markets: A High Frequency Perspective,* Working Paper, RGM Advisors, LLC

Chaboud, A., Chiquoine, B., Hjalmarsson, E., Vega, C., 2009, *Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market,* International Finance Discussion Papers – Board of Governors of the Federal Reserve System, #980.

Christie, A., A., 1982, The Stochastic Behavior of Common Stock Variances: Value, Leverage and Interest Rate Effects, *Journal of Finance, 3: 436-445*

Chuang, W. I., Hsiang, H. L., Susmel, R., 2011, *The Bivariate Approach to Investigating the Relation Between Stock Returns, Trading Volume, and Return Volatility,* Working Paper

Corradi, V., Distaso, W., Mele, A., 2009, *Macroeconomic Determinants of Stock Market Volatility and Volatility Risk Premia,* Working Paper

Cvitanic, J., Kirilenko, A. A., 2010, *High Frequency Traders and Asset Prices*, Working Paper, California Institute of Technology

Davidian, M., Carroll, R. J., 1987, Variance Function Estimation, *Journal of American Statistical Association, 82: 1079-1091*

Davis, N., Kutan, A.M., 2003, Inflation and Output as Predictors of Stock Returns and Volatility: International Evidence, *Applied Financial Economics, 13: 693-700*

De Long, B. J., Shleifer, A., Summers, L. H., Waldman, R. J., 1990, Noise Trader Risk in Financial Markets*, Journal of Political Economy, 980(4): 703-738*

Du, J., Wei, S. J., 2004, Does Insider Trading Raise Market Volatility?, *The Economic Journal, 114: 916-942*

Engle, R. F., 1982, Autoregressive Conditional Heteroscedasticity With Estimates of the Variance of United Kingdom Inflation, *Econometrica, 50(4), 987-1007*

Engle, R. F., Rangel,J.G., 2005, *The Spline GARCH Model for Unconditional Volatility and its Global Macroeconomic Causes,* Working Paper

Froot, K.A., Scharfstein, D.S., Stein, J.C., 1992, Herd On The Street: Informational Inefficiencies In a Market with Short-Term Speculation, *Journal of Finance, 47(4):1461–1484*

Garcia, F.V., Liu,L., 1999, Macroeconomic Determinants of Stock Market Development, *Journal of Applied Economics*, *2: 29-59*

Granger, C., 1969, Investigating Causal Relations by Economic Models and Cross Spectral Methods, *Econometrica, 37: 424-438*

Groth, S. S., 2011, *Does Algorithmic Trading Increase Volatility? Empirical Evidence from the Fully-Electronic Trading Platform Xetra*, Goethe University Frankfurt, Working Paper

Harris, L., 1986, Cross-Security Tests of the Mixture of Distribution Hypothesis, *Journal of Financial and Quantitative Analysis, 21: 39-46*

Harris, L., 1987, Transaction Data Tests of the Mixture of Distribution Hypothesis, *Journal of Financial and Quantitative Analysis, 22: 127-141*

Hasbrouck, J., 1991a, Measuring the Information Content of Stock Trades, *Journal of Finance, 46: 177-207*

Hasbrouck, J., 1991b, The Summary of Informativeness of Stock Trades: An Econometric Analysis, *Review of Financial Studies, 4: 571-595*

Hasbrouck, J., Saar, G., 2010, *Low-Latency Trading,* New York University, Working Paper

Hendershott, T., Jones, C., Menkveld, A., 2011, Does Algorithmic Trading Improve Liquidity? *Journal of Finance,. 66:1*

Hendershott, T., Riordan, R., 2009, *Algorithmic trading and Information,* NET Institute Working Paper #09-08

Hendershott, T., Riordan, R., 2011, *High Frequency Trading and Price Discovery,* Working Paper

Heston, S. L., 1993, A Closed-Form Solution for Options with Stochastic Volatility with Applications to Bond and Currency Options, *Review of Financial Studies, 6: 327-343*

Hirschey, N. H., 2011, *Do High-Frequency Traders Anticipate Buying and Selling Pressure?,* University of Texas at Austin, Job Working Paper,

Jovanovic, B., Menkveld, A. J., 2010, *Middlemen in Limit Order Markets,* VU University Amsterdam, Working Paper

Kearney, C., Daly, K., 1998, The Causes of Stock Market Volatility in Australia, *Applied Financial Economics, 8: 597-60*

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

Koutmos, G., Unro, L., Theodossiou, p., 1994, Time-Varying Betas and Volatility Persistence in International Stock Markets, *Journal of Economics and Business, 46: 101-112*

Koutoulas, G., Kryzanowski, L., 1996, Macrofactor Conditional Volatilities, Time-Varying Risk Premia and Stock Return Behavior, *The Financial Review, 31(1), 169-195*

Kyröläinen, P., 2008, Day Trading and Stock Price Volatility, *Journal of Economics and Finance, 32: 75-89*

Levine, R., Zervos,S., 1998, Stock Markets, Banks, and Economic Growth, *The American Economic Review, 88: 537-558*

Liljeblom, E., Stenius, M., 1997, Macroeconomic Volatility and Stock Market Volatility: Empirical Evidence on Finnish Data, *Applied Financial Economics, 7(4): 419-426*

Martinez, V., Rosu, I., 2011, *High Frequency Traders, News and Volatility*, Working Paper

Murphy, E. M., 2010, *Concept Release on Equity Market Structure*, Report Release, Securities and Exchange Commission

Nelson, D. B., 1991, Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica, 59: 347-370*

Parkinson, M., 1980, The Extreme Value Method for Estimating the Variance of the Rate of Return, *Journal of Business, 53: 61-65*

Pontiff, J., 1996, Costly Arbitrage: Evidence from Close-End Funds, *The quarterly Journal of Economics, 111: 1135-1151*

Saryal, F.S., 2007, Does Inflation Have an Impact on Conditional Stock Market Volatility?: Evidence from Turkey and Canada, *Journal of Economics and Finance, 11: 123-133*

Schwert, G.W., 1989a, Why Does Stock Market Volatility Change over Time? *Journal of Finance, 44: 1115-1153*

Schwert, G.W., 1989b, Business Cycles, Financial Crises and Stock Volatility, *Carnegie-Rochester Conference Series on Public Policy, 31: 83-125*

Shleifer, A., Vishny, R.W., 1997*,* The Limits of Arbitrage, *The Journal of Finance, 2: 35-55*

Tahir, M. F., Keung, W. W., *Linkage between Stock Market Prices and Exchange Rate: A Causality Analysis for Pakistan,* National University of Singapore, Working Paper

Vives, X., 1995, Short-Term Investment and the Informational Efficiency of the Market, *Review of Financial Studies, 8(1):125–160*

Walid, C., Chaker, A., Masood, A., 2011, Stock Market Volatility and Exchange Rates in Emerging Countries: A Markov-State Switching Approach, *Emerging Markets Review, 12: 272-293*

Wang, X., 2010, The Relationship between Stock Market Volatility and Macroeconomic Volatility: Evidence from China, *International Research Journal of Finance and Economics, 49:149-160*

Xiao, J., Brooks, R.D., 2009, GARCH and Volume Effects in the Australian Stock Markets, *Annals of Financial Economics, 5: 79-105*

**Electronic Sources and Reports**

AFM, 2010, High Frequency Trading: The application of advanced trading technology in the European marketplace, viewed 15 May 2012, http://www.afm.nl/layouts/afm/default.aspx~/media/files/rapport/2010/hft-report-engels.ashx

IMF, 2012, Special Drawing Rights, viewed 4 May 2012, http://www.imf.org/external/np/exr/facts/sdr.htm

Johansson, N., 2012, High Frequency Trading och Algoritmisk Handel - En Översikt, Rapport till Finansinspektionen, viewed 2 May 2012, http://www.fi.se/upload/43_Utredningar/20_Rapporter/2012/extrernrapport_hft.pdf

NASDAQ OMX Nordic, 2011, Market Model, viewed April 20 2012, http://www.nasdaqomx.com/digitalAssets/73/73614_nasdaq_omx_nordic_market_model_2.2_1_april_2011.pdf

# Appendices

Appendix I *(a)*

*Pair-wise Correlation **OMXS** (Monthly Data)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) $\text{Volatility}_{HL}$ | 1.00 | | | | | | | | |
| (2) $\text{Volatility}_{SD}$ | 0.95 | 1.00 | | | | | | | |
| (3) Log of Money Supply (M2) | 0.14 | 0.15 | 1.00 | | | | | | |
| (4) Exchange Rate Volatility | 0.53 | 0.65 | -0.20 | 1.00 | | | | | |
| (5) Interest Rate Volatility | -0.21 | -0.27 | -0.51 | -0.01 | 1.00 | | | | |
| (6) Inflation Volatility | -0.13 | -0.10 | 0.32 | -0.27 | -0.19 | 1.00 | | | |
| (7) Industrial Production Volatility | -0.29 | -0.24 | 0.09 | -0.36 | -0.22 | 0.32 | 1.00 | | |
| (8) Terms of Trade Volatility | -0.03 | -0.05 | 0.24 | -0.02 | 0.02 | 0.17 | -0.20 | 1.00 | |
| (9) Log of Turnover | 0.34 | 0.33 | -0.32 | 0.29 | -0.10 | -0.21 | -0.03 | -0.01 | 1.00 |
| **(10) HFTs' Fraction of Trading** | **0.64** | **0.63** | **0.62** | **0.28** | **-0.56** | **-0.02** | **-0.08** | **-0.03** | **-0.12** |

Appendix I *(b)*

*Pair-wise Correlation **OMXC** (Monthly Data)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) $\text{Volatility}_{HL}$ | 1.00 | | | | | | | | |
| (2) $\text{Volatility}_{SD}$ | 0.93 | 1.00 | | | | | | | |
| (3) Log of Money Supply (M2) | 0.03 | 0.10 | 1.00 | | | | | | |
| (4) Exchange Rate Volatility | 0.51 | 0.53 | 0.28 | 1.00 | | | | | |
| (5) Interest Rate Volatility | 0.48 | 0.48 | 0.03 | 0.26 | 1.00 | | | | |
| (6) Inflation Volatility | -0.08 | -0.17 | 0.02 | 0.04 | -0.14 | 1.00 | | | |
| (7) Industrial Production Volatility | -0.46 | -0.42 | -0.06 | -0.41 | 0.13 | -0.11 | 1.00 | | |
| (8) Terms of Trade Volatility | 0.18 | 0.18 | -0.73 | -0.12 | 0.14 | 0.04 | -0.03 | 1.00 | |
| (9) Log of Turnover | 0.11 | 0.14 | 0.29 | 0.20 | -0.21 | -0.19 | 0.11 | -0.29 | 1.00 |
| **(10) HFTs' Fraction of Trading** | **0.42** | **0.35** | **-0.71** | **-0.02** | **0.39** | **0.04** | **-0.12** | **0.86** | **-0.47** |

Appendix I *(c)*

*Pair-wise Correlation **OMXH** (Monthly Data)*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| (1) $\text{Volatility}_{HL}$ | 1.00 | | | | | | | | |
| (2) $\text{Volatility}_{SD}$ | 0.92 | 1.00 | | | | | | | |
| (3) Log of Money Supply (M2) | 0.39 | 0.42 | 1.00 | | | | | | |
| (4) Exchange Rate Volatility | 0.33 | 0.39 | -0.09 | 1.00 | | | | | |
| (5) Interest Rate Volatility | -0.01 | -0.10 | -0.10 | 0.02 | 1.00 | | | | |
| (6) Inflation Volatility | -0.14 | -0.09 | 0.06 | 0.04 | 0.07 | 1.00 | | | |
| (7) Industrial Production Volatility | 0.00 | -0.06 | -0.01 | -0.07 | -0.10 | 0.08 | 1.00 | | |
| (8) Terms of Trade Volatility | 0.07 | 0.28 | 0.10 | 0.36 | -0.29 | 0.08 | 0.14 | 1.00 | |
| (9) Log of Turnover | -0.06 | 0.00 | -0.39 | 0.07 | 0.12 | -0.12 | -0.28 | -0.15 | 1.00 |
| **(10) HFTs' Fraction of Trading** | **0.59** | **0.61** | **0.81** | **0.07** | **-0.08** | **0.04** | **-0.22** | **0.07** | **-0.31** |

Appendix II

| *Pair-wise Correlation Matrix (Daily Data)* | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Conditional Volatility (%)* | | | | | | |
| (1) Stockholm Stock Exchange | 1.00 | | | | | |
| (2) Copenhagen Stock Exchange | | 1.00 | | | | |
| (3) Helsinki Stock Exchange | | | 1.00 | | | |
| *Log of Market Turnover* | | | | | | |
| (4) Stockholm Stock Exchange | 0.26 | | | 1.00 | | |
| (5) Copenhagen Stock Exchange | | 0.07 | | | 1.00 | |
| (6) Helsinki Stock Exchange | | | -0.01 | | | 1.00 |
| *HFTs' Fraction of Trading (%)* | | | | | | |
| (7) Stockholm Stock Exchange | 0.63 | | | -0.07 | | |
| (8) Copenhagen Stock Exchange | | 0.54 | | | -0.31 | |
| (9) Helsinki Stock Exchange | | | 0.66 | | | -0.26 |

Appendix III *(a)*

*Stock Market Volatility, Market Activity and HFT Activity (**OMXS**)*

| | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{HL}}$ | | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{SD}}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **HFTs' Fraction of Trading (%)** | **1.88 (0.48)*** | **2.34 (0.52)*** | **1.60 (0.41)*** | **1.62 (0.42)*** |
| Log of Turnover | | 0.34 (0.12)*** | | 0.23 (0.10)** |
| Inflation Volatility (%) | | 1.72 (2.63) | | 1.89 (2.15) |
| Exchange Rate Volatility (%) | | 0.53 (0.36) | | 0.85 (0.29)*** |
| Interest Rate Volatility (%) | | 0.51 (0.30) | | 0.22 (0.24) |
| Constant | 0.04 (0.06) | -8.06 (2.75)*** | 0.04 (0.05) | -5.45 (2.25)** |
| No. of Observations | 25 | 25 | 25 | 25 |
| Adj. R-squared | 0.38 | 0.61 | 0.37 | 0.65 |
| Jarque-Bera statistic [a] | | 0.53 [0.767] | | 1.43 [0.488] |
| Breusch-Godfrey F-statistic (2 lags) | | 0.26 [0.774] | | 0.80 [0.464] |
| ARCH-test F-statistic (1 lag) | | 0.61 [0.443] | | 0.49 [0.491] |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

[a] Probability is denoted within [..]. Null-hypothesis implies there is no problem with the respective test statistic.

Appendix III *(b)*

*Stock Market Volatility, Market Activity and HFT Activity (**OMXC**)*

| | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{HL}}$ | | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{SD}}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **HFTs' Fraction of Trading (%)** | **1.46 (0.65)** | **3.81 (1.22)*** | **0.97 (0.54)*** | **1.92 (1.08)*** |
| Log of Turnover | | 0.19 (0.08)** | | 0.13 (0.07)* |
| Terms of Trade Volatility (%) | | -7.67 (3.82)* | | -2.98 (3.39) |
| Exchange Rate Volatility (%) | | 2.03 (0.89)** | | 1.78 (0.79)** |
| Interest Rate Volatility (%) | | 0.38 (0.50) | | 0.52 (0.44) |
| Constant | 0.14 (0.04)*** | -3.97 (1.68)** | 0.13 (0.03)*** | -2.75 (1.49)* |
| No. of Observations | 25 | 25 | 25 | 25 |
| Adj. R-squared | 0.14 | 0.54 | 0.09 | 0.42 |
| Jarque-Bera statistic [a] | | 1.54 [0.462] | | 1.46 [0.483] |
| Breusch-Godfrey F-statistic (2 lags) | | 0.65 [0.536] | | 0.55 [0.586] |
| ARCH-test F-statistic (1 lag) | | 0.10 [0.755] | | 1.39 [0.251] |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

[a] Probability is denoted within [..]. Null-hypothesis implies there is no problem with the respective test statistic.

Appendix III *(c)*

*Stock Market Volatility, Market Activity and HFT Activity (**OMXH**)*

| | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{HL}}$ | | Dependent Variable: $\boldsymbol{VOL}_{\mathbf{SD}}$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **HFTs' Fraction of Trading (%)** | **2.37 (0.67)*** | **2.44 (0.68)*** | **2.00 (0.54)*** | **2.19 (0.52)*** |
| Log of Turnover | | 0.07 (0.11) | | 0.09 (0.09) |
| Exchange Rate Volatility (%) | | 2.33 (1.35) | | 2.30 (1.04)** |
| Constant | 0.04 (0.07) | -1.62 (2.26) | 0.04 (0.05) | -2.01 (1.73) |
| No. of Observations | 25 | 25 | 25 | 25 |
| Adj. R-squared | 0.33 | 0.37 | 0.34 | 0.45 |
| Jarque-Bera statistic [a] | | 6.59[b][0.037] | | 1.31 [0.520] |
| Breusch-Godfrey F-statistic (2 lags) | | 0.62[0.548] | | 1.59 [0.230] |
| ARCH-test F-statistic (1 lag) | | 0.02 [0.898] | | 0.11 [0.746] |

Standard errors are in the parentheses. ***, **, and * denote statistically significant at the 1%, 5%, and 10% levels, respectively.

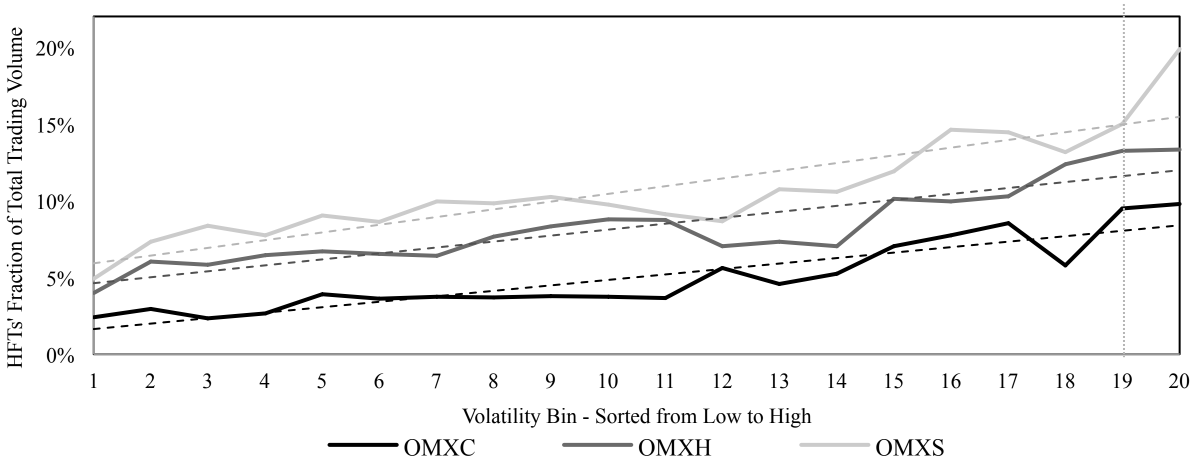
[a] Probability is denoted within [..]. Null-hypothesis implies there is no problem with the respective test statistic.

[b] Only regression for which the null-hypothesis, implying the residuals are normally distributed, is rejected within a 95% confidence level.

Appendix IV *(a)*

*Conditional Stock Market Volatility and HFTs' Fraction of Total Trading*

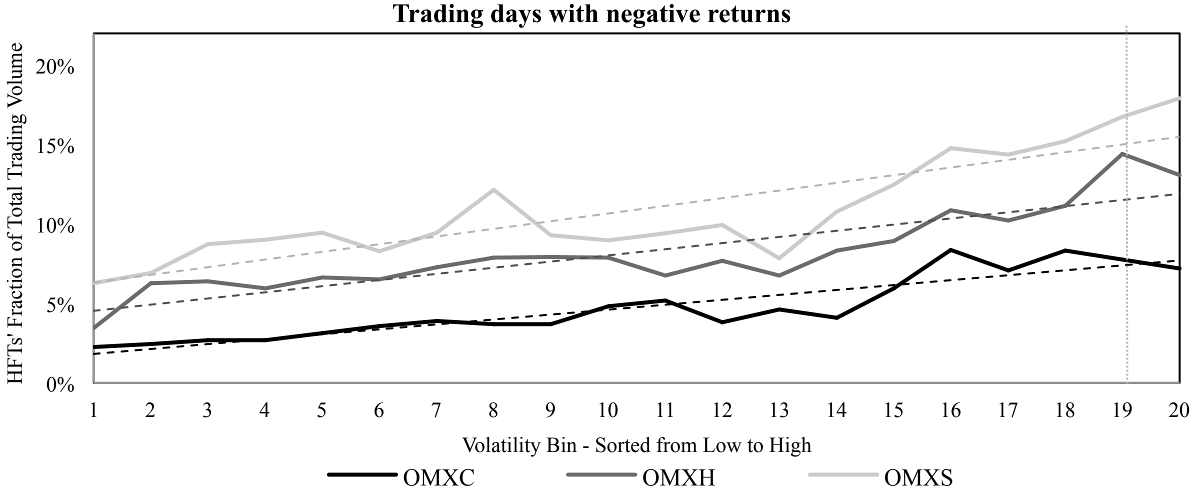
**Trading days with positive returns**




Appendix IV *(b)*

*Conditional Stock Market Volatility and HFTs' Fraction of Total Trading*

**Trading days with negative returns**




Appendix IV *(c)*

*Daily High-Low Market Volatility (**$VOL_{HL}$**) and HFTs' Fraction of Total Trading*