Vaasan yliopisto
UNIVERSITY OF VAASA

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Nordic Stock Price Informativeness in the Era of High-Frequency Trading

School of Accounting and Finance
Master's Thesis in Finance
Master's Degree Programme in Finance

Vaasa 2023

UNIVERSITY OF VAASA
School of Accounting and Finance

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Title of the Thesis:	Nordic Stock Price Informativeness in the Era of High-Frequency Trading
Degree:	Master of Science in Economics and Business Administration
Programme:	Master's Degree Programme in Finance
Supervisor:	Stig Xenomorph, Timo Rothovius
Year:	2023 **Pages:** 105

ABSTRACT:
The purpose of this thesis is to examine how high-frequency trading (HFT) affects long-term stock price informativeness in the Nordic equity markets. HFT is one of the most remarkable market microstructure advances in the 21st century covering a substantial share of trading volume in modern financial markets. HFT has gathered broad attention among researchers and regulators, but the views are disputed regarding HFTs' influence on market efficiency. The research field generally agrees that HFT benefits short-term price discovery by enhancing information incorporation, limiting pricing errors, raising liquidity, narrowing spreads, and reducing trading costs. HFT liquidity supply also mitigates short-term volatility, although there are controversialities on how HFT behaviour contributes to liquidity during severe uncertainty.

Yet, HFT's influence on long-term price informativeness is a much less studied area. Some recent studies suggest that the millisecond improvements in price discovery are achieved at the expense of mitigated information acquisition. This could erode price informativeness and thus productive resource allocation in the long term. The major concern is that instead of acquiring new information, HFT speculation relies on already existing public information and statistical millisecond correlations that are not necessarily related to fundamentals. HFTs' ability to predict order flows also makes information acquisition less profitable for other informed traders. Some HFTs even follow predatory strategies that hamper the order execution. Many concerns also relate to dark trading that could potentially diminish market efficiency because in excessive levels it increases adverse selection and mitigates liquidity in traditional exchanges.

To address this contradiction, this thesis examines how HFT presence in Nordic markets affects stock price informativeness regarding future cash flows in one to five-year forecasting horizons. Staggered difference-in-differences tests provide exceptional results indicating that stock prices become slightly more sufficient estimates of future cash flows after HFTs enter markets in Denmark, Finland, Norway, and Sweden. The enhanced price informativeness is observed mostly among small firms whereas large firms are unaffected by the HFT presence. HFTs improve price informativeness, especially during economic downturns which indicates that they remain consistent in liquidity supply and even shift trading to small stocks in volatile circumstances. These results propose that advanced price discovery eventually outweighs the potential reductions of information acquisition in the Nordic markets. Fundamental information is incorporated into prices more effectively after its public announcement and thus stock prices reflect even more successfully companies' long-term productivity.

KEYWORDS: high-frequency trading, price informativeness, information acquisition, market microstructure

VAASAN YLIOPISTO
Laskentatoimen ja rahoituksen yksikkö

Tekijä:	Rea Sjögren
Tutkielman nimi:	Nordic Stock Price Informativeness in the Era of High-Frequency Trading
Tutkinto:	Kauppatieteiden maisteri
Oppiaine:	Rahoitus
Työn ohjaaja:	Stig Xenomorph, Timo Rothovius
Vuosi:	2023 **Sivumäärä:** 105

TIIVISTELMÄ:
Tämän tutkielman tarkoituksena on tutkia huippunopean algoritmikaupan (HFT) vaikutuksia osakekurssien pitkän aikavälin informatiivisuuteen pohjoismaisilla osakemarkkinoilla. HFT on yksi 2000-luvun merkittävimmistä edistysaskeleista markkinoiden mikrorakenteessa ja se kattaa huomattavan osuuden modernien rahoitusmarkkinoiden kaupankäyntivolyymista. HFT on herättänyt laajasti huomiota tutkijoiden ja sääntelyviranomaisten keskuudessa, mutta näkemykset sen vaikutuksista markkinoiden tehokkuuteen ovat ristiriitaisia. HFT tutkimukset ovat enimmäkseen yksimielisiä siitä, että HFT tehostaa lyhyen aikavälin hinnanmuodostusta edistämällä tiedon kulkeutumista hintoihin, vähentämällä hinnoitteluvirheitä, kasvattamalla likviditeettiä, kaventamalla osto- ja myyntitarjousten välistä eroa sekä alentamalla kaupankäyntikustannuksia. HFT-kauppiaiden tuottama likviditeetti vähentää myös lyhyen aikavälin volatiliteettia. On kuitenkin kiistanalaista, kuinka HFT vaikuttaa likviditeettiin erittäin epävakaissa markkinaolosuhteissa.

HFT:n vaikutuksia pitkän aikavälin hintainformatiivisuuteen on tutkittu tähän mennessä huomattavasti vähemmän. Viimeaikaisten tutkimuksien mukaan millisekuntien parannukset hinnanmuodostuksessa saavutetaan vähentyneen tiedonhankinnan kustannuksella. Tämä voi heikentää hintojen informatiivisuutta ja siten tuottavaa resurssien allokointia pitkällä aikavälillä. Suurin huolenaihe on, että uuden tiedon hankkimisen sijaan HFT-spekulaatio perustuu jo olemassa olevaan julkiseen tietoon sekä tilastollisiin millisekunnin korrelaatioihin, jotka eivät välttämättä liity fundamenttitekijöihin. HFT-kauppiaiden kyky ennakoida tilausvirtoja tekee tiedon hankinnasta vähemmän kannattavaa muille markkinaosapuolille. Osa HFT-kauppiaista myös hyödyntää saalistusstrategioita, jotka haittaavat perinteisten sijoittajien kaupankäyntiä. Huolta herättää myös dark pool -kauppa, joka voi liiallisissa määrin heikentää markkinatehokkuutta lisäämällä haitallista valikoitumista ja vähentämällä likviditeettiä perinteisissä pörsseissä.

Tämän ristiriidan selvittämiseksi tässä tutkielmassa tarkastellaan, kuinka HFT vaikuttaa pohjoismaisten osakkeiden hintainformatiivisuuteen tulevaisuuden kassavirroista 1-5 vuoden ennustehorisonteissa. Porrastettujen difference-in-differences -testien poikkeukselliset tulokset osoittavat, että osakkeiden hinnoista tulee aiempaa tarkempia arvioita tulevaisuuden kassavirroista HFT:n tultua markkinoille Tanskassa, Suomessa, Norjassa ja Ruotsissa. Hintojen informatiivisuus kasvaa lähinnä pienissä osakkeissa, kun taas suurien yhtiöiden hintainformatiivisuudessa ei havaita merkittävää muutosta. HFT lisää hintainformatiivisuutta erityisesti talouskriiseissä, mikä osoittaa, että HFT:t jatkavat johdonmukaista likviditeetin tarjontaa ja jopa käyvät enemmän kauppaa pienillä osakkeilla epävakaissa markkinaolosuhteissa. Nämä tulokset viittaavat siihen, että pohjoismaissa HFT edistää hinnanmuodostusta enemmän kuin haittaa uuden tiedon hankintaa. Osakekurssit reagoivat entistä tehokkaammin julkisiin tiedonantoihin ja näin ollen osakkeiden hinnat heijastavat todenmukaisemmin yhtiöiden tuottavuutta myös pitkällä aikavälillä.

AVAINSANAT: huippunopea algoritmikauppa, hintainformatiivisuus, tiedonhankinta, markkinoiden mikrorakenne

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1 Introduction

High-frequency trading (HFT) is a relatively new phenomenon in finance and one of the most remarkable market microstructure developments in 21st century financial markets. Increased automatization and algorithmic trading (AT) in financial markets have resulted in the rise of new automated intermediaries called high-frequency traders (HFTs) who have overthrown traditional human market makers in financial markets (Brogaard et al., 2014). Thus, markets have become more fragmented, complex and faster which highlights the importance of market microstructure (O'Hara, 2015). Market microstructure is a growing research field in finance which examines the functioning of financial markets including exchange structuring, trading behaviour, determinants of spreads and quotes, transaction costs, liquidity, and price discovery.

HFTs are considered a subset of algorithmic traders (ATs) as they use complicated algorithms to fulfil their followed strategies and to analyse market data in high velocities (Aït-Sahalia & Brunetti, 2020; Brogaard et al., 2014; Hasbrouck & Saar, 2013). HFT algorithms make strategic decisions between market and limit orders, choosing whether to split them across time or trading venues and whether they are submitted or cancelled (Aït-Sahalia & Brunetti, 2020). All this is performed within milliseconds and without human intervention. U.S. Securities and Exchange Commission (SEC) (2010) defines HFT as a mechanism that uses extraordinary high-speed and sophisticated computer programs to transact a large number of orders in extremely short time frames. HFTs also tend to cancel many of these orders soon after they are submitted and end a day with a flat position meaning that they do not carry positions overnight (SEC, 2010).

HFTs constantly seek ways of minimizing network and other latencies to achieve the lowest possible latencies so that they can produce millisecond responses to market events. Latency is the time it takes computer algorithms to learn about a new event, create a response, and finally execute an order in the exchange (Hasbrouck & Saar, 2013). Pursuing low latencies has led to an arms race of ongoing technology upgrades and co-locating computers near trading venues to gain superior informational and operational advantage. With co-locating, HFTs aim to reduce the distance between their computers and exchanges to speed up data transfer time. This is executed by renting premises near trading venues, although HFTs have located themselves near exchanges already years before exchanges began to rent premises (Aitken et al., 2015). These efforts for low latencies enable a remarkable decline in transmission times and thus the quickest HFTs reach a latency of 2-3 milliseconds (Hasbrouck & Saar, 2013).

1.1 Background and motivation

HFTs have a major role in equity markets given their large share of trading volume. Their market volumes range widely but according to the SEC (2010), HFTs typically cover at least half of the overall trading volume in U.S. equity markets. Carrion (2013) reports that HFTs account for up to 68% of Nasdaq's trading volume value. In Europe, the equivalent HFT share is 24–43% of the overall trading volume (European Securities and Markets Authority ESMA, 2014). Whilst in Sweden, HFTs cover 25–50% of trading volume (Hagströmer & Nordén, 2013). Hence, HFT has gathered a lot of attention among researchers and regulators in recent years and the views about the implications of HFT on market quality are divided. The empirical research generally suggests that HFT improves market efficiency as it enhances information incorporation into prices, reduces pricing errors, provides liquidity, narrows bid-ask spreads, reduces transaction costs and mitigates short-term volatility (Aït-Sahalia & Brunetti, 2020; Hasbrouck & Saar, 2013; Ke & Zhang, 2020). According to Brogaard et al. (2014), HFTs improve price discovery by trading in line with permanent price changes and against transitory pricing errors.

Yet, the above improvements in price discovery are observed in a millisecond horizon which is not necessarily relevant for traditional investors and corporations who generally make investment decisions in a much longer perspective (Chordia & Miao, 2020). Empirical studies regarding the long-term effects of HFT are still scarce and it remains unclear if these improvements in price discovery also apply at the lower frequencies of non-HFTs. Moreover, some studies are concerned that HFT may potentially erode sufficient capital markets. Caused by their superior speed advantage, HFTs may lead to unfair competition and disruptive trading behaviour (Aït-Sahalia & Brunetti, 2020). It is also stated that HFTs' beneficial price impacts are mainly transitory because of the short-lived tendency of their strategies (Ke & Zhang, 2020). The strategies of such nature lean on statistical correlations of stock returns instead of incorporating fundamental information into the prices.

Previous studies mainly focus on how HFT affects incorporating existing information into prices while the acquisition of new information is mostly disregarded. Weller (2018) introduces that HFT poses a contradiction between the two aspects of price discovery: acquiring new information and incorporating existing information into prices. The author provides novel evidence showing that while HFT furthers the incorporation of the available information into prices, it reduces the acquisition of new acquirable information. Observed lack of information acquisition persists at least a month before earnings announcements whereas enhancements of price discovery are measured in a millisecond environment post-announcement. Lee and Watts (2021) obtain similar results as they study whether an increase in tick size impacts HFT activity. They discover that while HFT activity declines as tick size rises, fundamental investors increase their information acquisition before and around earnings announcements. Gider et al. (2019), on the other hand, examine information acquisition from a longer-term perspective of fundamental prices. Consistently with Weller (2018) and Lee and Watts (2021), the authors find that stock price informativeness regarding their intrinsic values declines after HFTs enter the market.

The above findings should be taken into closer consideration as reduced price informativeness eventually erodes social welfare. Inefficient prices prevent sufficient capital allocation due to limited resources and budget constraints, leading to less informed investment decisions due to declined managerial learning from prices while exposing to greater systematic risk (Baker et al., 2003; Chen et al., 2007; O'Hara, 2003). Moreover, Hirshleifer (1971) states that the discovery of new information is more relevant for asset allocation than faster incorporation of already existing information into prices.

1.2 Purpose of the study

The purpose of this thesis is to study the long-term effects of HFT on fundamental stock price informativeness and especially on information acquisition. HFT studies so far have mainly concentrated on the price efficiency of already existing information. However, only a little attention has been paid to the information acquisition among HFT research considering that these millisecond improvements in price discovery seem to be realized at the expense of reduced information acquisition. This raises concerns since the acquisition of new information plays a crucial role in determining intrinsic values. According to Fama (1970), security prices should truthfully reflect all available information to provide correct signals for companies and investors who make production or investment decisions. If asset prices draw away from their fundamental values, the core purpose of financial markets could be endangered. Above all, financial markets should produce maximum welfare by allocating limited resources to the most productive participants of society. Therefore, HFT's effects on information acquisition require further research.

This thesis examines how precisely stock prices resemble their fundamental values after HFTs enter the market. Using the staggered difference-in-differences (DiD) method, this study compares stock price informativeness about future cash flows before and after HFT presence in Nordic stock markets. The research methodology is based on the work of Gider et al. (2019), but instead of studying international markets, this paper focuses solely on the Nordic stock market including Denmark, Finland, Norway, and Sweden. These four Nordic welfare countries provide research setting with minimal cross-country differences due to their strong economic relations, shared culture, harmonized exchanges, and closely related regulation, taxation and accounting policies (Booth et al., 1997).

This thesis contributes to HFT literature with additional empirical insight regarding the little-studied effects of HFT on long-term price informativeness. Prior HFT research mainly covers the short-term price discovery of already existing information while only a few papers consider the acquisition of new information and thus long-term price informativeness. To extend the work of Lee and Watts (2021), Weller (2018) and Gider et al. (2019), this thesis aims to provide additional empirical evidence on how HFT presence affects information acquisition and fundamental stock price informativeness.

Furthermore, HFT studies are often located in the U.S. market whereas the Nordic market is a much less examined area. Thus, this thesis offers a more extensive view of HFT's effects on price efficiency in the Nordic stock market. Weller (2018) and Lee and Watts (2021) examine HFT and price informativeness in the U.S. market whereas Gider et al. (2019) cover this subject internationally. The empirical strategy of this thesis follows Gider et al. (2019) who also include Sweden and Norway in their global data set. However, this thesis contributes with novel evidence regarding Finnish and Danish stock markets, and by using a more homogeneous data set of the Nordic stock market.

1.3 Hypotheses

Weller (2018) creates a new price jump ratio measure to examine relative information acquisition. It shows how much information is incorporated into prices before an earnings announcement is published: the bigger the jump during the announcement, the less information has been acquired before its public revelation. The price jump ratio is regressed with commonly recognized AT proxies such as odd-lot ratio, trade-to-order ratio, cancel-to-trade ratio, and small average trade size (see e.g., Hagströmer & Nordén, 2013; Hendershott et al., 2011; O'Hara et al., 2014). These typical indicators of HFT activity are also used in studies by Aitken et al. (2015) and Lee and Watts (2021). Weller (2018) finds a significant negative correlation between AT and the acquisition of new information prior announcement period. Information content of prices declines 9–13% per one additional standard deviation of AT activity. These reductions are observed up to a month before earnings announcements and as the moment of announcement gets closer, high-HFT stocks become increasingly less informative compared to low-HFT stocks.

Lee and Watts (2021) obtain supporting results as they study the effects of larger tick sizes on AT around earnings announcements news. Utilizing the Tick Size Pilot program, the authors discover that a larger tick size reduces AT activity leading to increased information acquisition pre-announcement period. Results show that declined HFT activity increases standardized unexpected earnings (SUEs) up to 60 trading days before an announcement while simultaneously reducing price synchronicity. The authors also test a post-earnings announcement drift (PEAD) and find no slowdown in price discovery after the announcement. This indicates an overall improvement in price informativeness as more price discovery is already done before the announcement when HFTs are less active. However, it should be noted that Lee and Watts (2021) are unable to show a causal relation between reduced HFT activity and enhanced price informativeness. A possibility exists that some alternative factors followed by larger tick size caused the observed improvements. Yet, the authors argue that cross-sectional variation is unlikely in the setting of the Tick Size Pilot.

Bhattacharya et al. (2020) present somewhat contradicting evidence stating that HFT furthers the incorporation of fundamental information into stock prices. Instead of using HFT proxies, the authors utilize the Nasdaq dataset that separates HFT trades from traditional trades. Their results show that HFT-traded stocks have larger earnings response coefficients (ERCs), which is a similar metric to SUE used in Lee and Watts (2021), and a more significant reduction in post-earnings price impact of trades which denotes a reduced level of information asymmetry. According to the authors, these results indicate that HFT enhances the incorporation of earnings information into prices after the announcement. However, this interpretation does not address the potentially declined information acquisition in the pre-announcement period discovered in the above studies. Furthermore, these findings are observed at considerably shorter post-announcement period spanning from three hours after the announcement to the end of the trading day, whereas Lee and Watts (2021) and Weller (2018) focus pre-announcement period spanning three to one month before the announcement.

The papers above study HFT and the incorporation of information around earnings announcements, but Gider et al. (2019) are the only ones to examine price informativeness at remarkably longer one-to-five-year horizons. Gider et al. (2019) utilize a welfare-based measure of price informativeness introduced by Bai et al. (2016) which measures the predicted variation of future cash flows from prevailing market prices. The measure indicates how successfully stock price reflects a company's expected profitability in the future. Gider et al. (2019) compare fundamental stock price informativeness before and after HFT entrance in 18 stock markets internationally. Their results indicate reduced stock price informativeness regarding future cash flows and investments. The effect is more pronounced in longer horizons. Consistently, Baldauf and Mollner (2020) suggest in their model that HFTs' passive and aggressive strategies negatively affect price informativeness by deducting incentives for information acquisition. Overall, most of these few previous studies suggest that HFT erodes information acquisition and therefore long-term stock price informativeness which leads to the first hypothesis of this thesis:

H_1: HFT reduces stock price informativeness about future cash flows.

The above studies ensure the robustness of their results by including price non-synchronicity as an additional measurement of price informativeness. Price synchronicity describes the proportion of which a stock's return is explained by market index and industry returns. Non-synchronicity is the residual illustrating unexplained firm-specific return variance. Yet, Roll (1988) discovers that public information measured by R-squared of systematic, industry and firm-specific factors explain only 35% of stock returns. The author proposes that either noise or private information could explain the remaining 65%. Durnev et al. (2003) find statistically significant empirical evidence supporting the latter. They show that stock prices with a higher proportion of firm-specific information resemble more accurately their fundamental values according to the company's future earnings. Morck et al. (2000) examine price synchronicity in emerging markets finding that due to poor property rights, less firm-specific information is acquired by informed traders and therefore stock prices become more synchronized. In conclusion, high stock price synchronicity equals reduced levels of firm-specific information and therefore less informed prices. Bhattacharya et al. (2020), Gider et al. (2019), Lee and Watts (2021), Malceniece et al. (2019) and Weller (2018) all detect a positive relation between HFT and price synchronicity. Thus, the second hypothesis of this thesis states the following:

H_2: HFT decreases stock price non-synchronicity.

1.4 Structure of the study

The rest of this thesis proceeds as follows. Chapter two introduces the theoretical framework of efficient market theory and stock price informativeness. Chapter three continues by presenting market and income-based asset pricing models which are relevant in comprehending stock valuation and price discovery. The extensive literature review in chapter four covers prior HFT research related to stock price informativeness and market efficiency. The chapter takes a closer view of HFTs' behaviour and their effect on price discovery, volatility, and acquisition of new information. Chapter five presents the data sample and methodology used in the empirical research of this thesis. Obtained results are discussed in chapter six and final conclusions are summarized in chapter seven.

2 Market efficiency and price informativeness

To fully understand the effects of HFT on price informativeness, one must be familiar with the efficient market theory and the concepts related to the model. This chapter introduces the theoretical framework of efficient markets and random walk, but also the reasons why market efficiency is not constantly fulfilled in practice. After that, the chapter describes the characteristics of informed traders and the adverse selection costs they impose on less informed traders. Finally, the chapter concludes by reviewing a general measure of price informativeness – price synchronicity and views of its interpretation.

2.1 The efficient market theory

Fama's (1970) efficient capital market theory states that in efficient markets security prices fully reflect all available information. According to the theory, market efficiency can appear in three different forms depending on the information that is incorporated into prices. In a weak form of market efficiency, prices reflect only historical information such as price or return sequences. A semi-strong form of efficiency occurs when prices incorporate other available public information for example corporate announcements, annual reports, or new security issues. When prices include all available information, including private information, market efficiency reaches its strongest form. However, Fama (1970) points out that the strong form should be seen more as a benchmark to detect market inefficiencies because it is never truly realized in practice. The two inefficiencies of this sort are corporate insiders' private information and market makers who take advantage of their monopolistic access to unexecuted limit orders to make profits (Fama, 1970).

In efficient markets, stock prices adapt quickly to new information and change only when new information arrives on the market. Fama's (1970) theory relies on the general assumption in finance: market equilibrium which can be observed in expected returns. According to Fama's (1991) theory, an information event should make an instant impact on prices without a delay. This can be measured by abnormal daily returns that are deviations from expected returns and indicate how fast prices adjust to the new information. These hypotheses are consistent with the fair game model according to which it should not be possible for market participants to gain excessive returns in the market. Without taking above-average risk, it is not possible to earn above-average returns (Malkiel, 2003). In other words, markets are efficient when prices adjust to new information immediately so that investors cannot achieve any abnormal risk-adjusted returns caused by pricing errors. According to Fama (1991), prices react efficiently to corporate-specific information such as investment decisions, dividend changes, adjustments in capital structure and corporate-control transactions.

Technical and fundamental analysis should become unavailing in efficient market conditions where news and other new information are immediately incorporated into prices (Malkiel, 2003). Technical analysis examines past price movements to find a pattern to forecast future prices whereas fundamental analysis compares companies' intrinsic values to their market values to discover undervalued stocks. Consequently, these methods should be useless in gaining abnormal returns in efficient market circumstances because prices should already include such information (Malkiel, 2003). Instead, investors who possess a randomly selected diversified stock portfolio with equal risk will achieve the same level of returns in the end.

2.2 Random walk

The efficiency of a market can be tested with the random walk tests. In efficient market conditions, stock prices should reflect all available information and only change when new information enters the market (Fama, 1965; Fama, 1970). Therefore, future price changes should be impossible to predict because new information cannot be known beforehand or otherwise the news would not be news by the definition (Malkiel, 2003). Hence, expected returns follow a random walk in which successive stock price changes and returns are independent and identically distributed (Fama, 1965; Fama, 1970). This means that there are no correlation patterns between past price returns and therefore future price changes cannot be predicted from the past. So, today's price changes reflect news today, and tomorrow's price changes will be completely independent from today's price changes reflecting only news of that current day (Malkiel, 2003). When prices follow a random walk, stock prices at any point in time should reflect estimates of companies' fundamental values which are the market's expectations about the value of all available information given that time (Comerton-Forde & Putniņš, 2015; Fama, 1965).

The random walk model is based on the perception that individual security prices reflect the informational events that have already occurred and the events that markets expect yet to come (Fama, 1965). However, rational market participants are rarely unanimous about the intrinsic values of stocks which creates uncertainty and leads to a gap between actual price and intrinsic value. Fama (1965) concludes that competing market participants cause the actual price to randomly wander around its intrinsic value. The intrinsic value, on the other hand, can only change due to new fundamental information and in efficient markets this information should be incorporated into prices instantly (Fama, 1965). Yet, this rarely holds in reality. Instead, prices often tend to over or under-adjust to their intrinsic values and this adjustment occurs with a delay that itself is a random variable (Fama, 1965). This creates the independent nature of successive price changes eliminating the possibility of using previous price patterns to predict future price changes. In conclusion, stock prices do not necessarily reflect their intrinsic values constantly, but the gap between intrinsic value and actual price should be random. These random deviations are equally likely to be over or under-rated making it impossible to predict them with any strategy nor to gain excessive returns from them.

2.3 Market efficiency in reality

The efficient market hypothesis has received some criticism as several financial economists argue that stock prices are predictable at least to some extent. According to the critics, there are psychological and behavioural factors in the markets, due to which the past stock price patterns and fundamental valuation measurements make forthcoming prices predictable (Malkiel, 2003). These so-called anomalies are deviations from market efficiency that may enable investors to gain abnormal returns. Empirical evidence indicate some short-term momentum and correlation between successive stock price movements in the market (Jegadeesh & Titman, 1993; 2001). According to Malkiel (2003), momentum can be explained in two ways: either with a psychological feedback mechanism in which people see stock prices rising and expect prices to keep growing or with investors' tendency to underreact on new information. However, the statistical dependencies that cause momentum are so slim that it would be very unlikely for investors to gain abnormal returns after transaction costs.

Malkiel (2003) suggests that markets can be efficient despite the irrational market participants, occasional pricing errors or excessively fluctuating prices. Even though prices are not fully accurate at all times, markets can be efficient at longer horizons. Malkiel (2003) suggests that even when pricing errors and predictable patterns occur, the true value will win in the long run. Moreover, price patterns cannot be employed to earn constant excess returns because these patterns tend to vanish over time. This is because pricing irrationalities are soon corrected by the market as investors exploit them in the hope of abnormal returns and so pricing errors do not persist too long.

However, some persistent patterns exist in financial markets as long-term stock returns are shown to be negatively correlated with past returns (Fama & French, 1988). Contrary to Fama's (1965) statement that prices are just as likely to over or underreact, later studies propose that stock prices rather tend to overreact and thus drift further away from their fundamental values which will eventually lead to mean reversion (DeBondt & Thaler, 1985; Fama & French, 1988; Summers & Poterba, 1988). Mean reversion illustrates excessive or subnormal returns that will eventually return to their average level in the long run. Yet, the studies of this matter are divided. Malkiel (2003) also expects that developments in financial markets will increase deviations from market efficiency. As databases get more sophisticated and statistical techniques more efficient, detecting return patterns gets easier and stock prices become more predictable.

2.4 Informed trader and information acquisition

Kyle (1985) describes an informed trader as a risk-neutral participant who uses unique access to private observation of the liquidation value of the asset to maximize expected returns. In addition, the author introduces two other kinds of traders: market makers and uninformed noise traders. Market makers set prices in the semi-strong sense of efficiency relying on the information provided by the traded quantities in the markets. Uninformed noise traders, on the other hand, trade randomly which means that their traded quantities are distributed independently from the past. Black (1986) describes noise as the opposite of information. Uninformed trading incorporates noise into stock prices driving prices further away from their intrinsic values. Nevertheless, noise is essential to financial markets because it creates liquidity in markets (Black, 1986). Informed insiders and noise traders place market orders by certain quantities they have decided to trade with (Kyle, 1985). After that, market makers clear the market by setting a price and trading the quantity which results in a combination of quantities traded by insiders and noise traders creating an order flow (Kyle, 1985). In conclusion, stock prices end up reflecting the information of informed traders and the noise of noise traders (Black, 1986).

Furthermore, Kyle (1989) suggests that the rational expectation equilibrium is not competitive; rational informed traders should be viewed as imperfect competitors who acknowledge the effects of their trading on prices. Kyle's (1989) model provides two reasons why informed traders act as imperfect competitors. First, speculative markets show that the most informed traders are large operators. Arbitrageurs with private information transact a remarkable proportion of public companies' equity in stock markets. So, most likely traders of this size affect prices but also consider the effects of their trading when choosing the quantities to trade with (Kyle, 1989). Secondly, if informed traders would behave as perfect competitors, prices would become too transparent revealing too much of their private information. This would limit their profits discouraging informed traders from acquiring expensive private information (Kyle, 1989). However, the model of imperfect competition removes the issues discussed above by keeping the prices inefficient enough for informed traders to create profits by acquiring costly private information (Kyle, 1989). In other words, informed traders possess a monopoly in the asset market and noise traders provide a shield to their trading because market makers cannot recognise them from another (Kyle, 1985). This enables insiders to gain profits at the expense of the noise traders. Although prices include the trade quantity of noise traders which follows random motion, the private information is incorporated into stock prices eventually due to the trading actions of insiders (Kyle, 1985).

French and Roll (1986) observe six times higher return volatility during exchange opening hours when most of the trading occurs. According to the authors, fundamental information is incorporated into stock prices through public announcements and trading activity of risk arbitrageurs. Prices react to public information instantly at the time of announcement as markets revaluate stock prices accordingly whereas private information is incorporated into prices via trades of risk arbitrageurs. Their empirical results show that private information causes most of the return variation along with increased public announcements during trading hours. Pricing errors, on the other hand, explain only 12% of the variance at the most.

According to Hirshleifer (1971), the value of already known information is in its priority relative to others which in time will be evident to all, whereas acquiring new information creates value through research and correct interpretation of the findings. Private information that remains private adds no social value because it has no impact on productive decisions, unlike public information that channels productive resources. By selling or speculating with private information, one can gain profits that provide an incentive to acquire new information. However, selling private information forward generally offers larger profits than speculative trades leading to socially wasteful private overinvestment (Hirshleifer, 1971).

Many of today’s market venues sell access to public information milliseconds before it is available to the general public. This turns public information into private information for a short period before its publication (O'Hara, 2015). However, even a fleeting moment is enough for sophisticated traders to utilize the information. HFTs can turn their speed advantage into information via co-location and technology. Therefore, superior speed gives HFTs an advantage in predicting price movements over other market participants (Aït-Sahalia & Brunetti, 2020; Brogaard et al, 2014; O'Hara, 2015). This is why HFTs can be considered as informed traders. According to O'Hara (2015), it is no longer obvious that informed traders necessarily rely on fundamental information in high-frequency conditions. Instead, during high intervals and co-location, information is not only asset-related but also order-related which means that a trader must also be faster than others to be informed (O'Hara, 2015).

2.5 Adverse selection cost

As introduced in the previous chapter, traders can be divided into different groups according to their level of obtained information. This segmentation of uninformed and informed traders means that there is information asymmetry in the markets which causes adverse selection. Akerlof (1970) created the automobile model to illustrate adverse selection. This classic model uses the market of used cars as an example where the buyer does not have all the same information about the quality of the car as the current owner and seller of the car. Therefore, the buyer cannot be sure about the quality of the car. Akerlof (1970) refers to bad cars as "lemons" and notes that since a buyer cannot distinguish a good car from bad cars, the lemons sell at the same price as good cars. Eventually, bad cars capture the market because of the greater profit prospects and consequently, they become adversely selected.

Akerlof (1970) also explains adverse selection cost with an insurance example in which people who know they will need insurance are more likely to get one. It is nearly impossible for insurance companies to define the actual risks involved with customers. Therefore, price levels start to rise when people with medical insurance are more likely in need of medical attention (Akerlof, 1970). Higher insurance prices, on the other hand, repel healthier people from getting insurance.

Brogaard et al. (2014) show that HFTs impose more adverse selection to non-HFTs' orders when demanding liquidity. HFTs' superior ability to process and trade on public information causes informational asymmetry that imposes other market participants to adverse selection costs (Brogaard et al., 2017). So, when new information arises, HFTs can use their speed advantage to switch their positions before non-HFTs manage to change their orders. In addition, HFTs manage to avoid some adverse selection costs themselves while supplying liquidity, meaning that HFTs are also adversely selected but less so when compared to other liquidity suppliers (Brogaard et al., 2014; Carrion, 2013).

2.6 Price synchronicity

Price synchronicity describes the co-movement of a stock's returns with market movements. R-squared (R^2) is a generally used measure of price synchronicity in finance indicating the extent to which stock return is explained by the market index. Roll (1988) uses R^2 to segregate firm-specific return variance from a stock's overall variance. The residual that cannot be explained by the market and industry factors describes unexplained firm-specific return variance also called idiosyncratic volatility. However, Roll (1988) shows that R^2 is insufficient in explaining stock return variation since industry, firm-specific and systematic economic factors cover only 35% of stock returns. The author suggests that either noise or private information might explain the residual 65%. Since then, views have been divided on whether price synchronicity equals improved or declined informativeness of stock prices. The generally prevailing view is that high price synchronicity results from a decreased level of firm-specific information and is associated with hampered price informativeness whereas some opposing studies suggest that informed prices can be increasingly synchronized.

Durnev et al. (2003) show empirical evidence indicating that stock returns of lower R^2 stocks resemble more closely the company's future earnings. They find a significant positive correlation between firm-specific return variation and stock price informativeness about future cash flows. This supports the view that current returns of less synchronized stocks are more informed about the company's fundamentals. Wurgler's (2000) results similarly suggest that a higher level of firm-specific information in stock returns is related to more efficient capital allocation. According to the author, prices that contain more firm-specific information act as sufficient public indicators for investors' investment decisions, resulting in more efficient capital allocation. Consistently, Morck et al. (2000) find that stock prices are more synchronized in developing economies because of the lack of property rights. Structural market characteristics such as market size, correlated company earnings, volatility of fundamentals or low level of economic diversification mostly fail to explain this effect. Instead, institutional factors are the source of this effect. The authors show that poor property rights reduce the incentives for firm-specific risk arbitrage while market-wide events and noise increase their influence on prices.

Jin and Myers (2006) further suggest that poor property rights alone do not necessarily affect synchronicity if the company is entirely transparent. According to the authors, investor property rights together with perceived information determine how risk is divided between investors and management. Even though investor rights would be fully secured, managers could make extensive captures of the firm's cash flows if investors are not fully informed about the company's true state and cash flows. Managers can make larger withdrawals if cash flows are larger than investors believe, but when cash flows are smaller than thought, managers might try to hide it by reducing their withdrawals. This shifts firm-specific risk from investors to the firm's management, leading to higher stock price synchronicity. Management that holds information also exposes the firm's stock to crash if all the hidden bad news is revealed to the public at once. More frequent crashes again result in higher synchronicity (Jin & Myers, 2006). Hence, lack of transparency and investor monitoring together increase price synchronicity if management holds firm-specific information.

Dasgupta et al. (2010), on the other hand, provide a model according to which returns become more synchronized along with increased transparency. According to their model, stock prices of transparent companies reflect expected future events more closely as more information is available. If these predictions are realised as expected, the surprise in the market is smaller and so is the price reaction. This means reduced firm-specific variation and more synchronized returns in the future. Dasgupta et al. (2010) obtain empirical evidence indicating that older companies have more synchronized returns because over time markets learn about the constant characteristics of a company. Furthermore, return synchronicity is shown to increase among seasoned equity offered (SEO) and cross-listed companies because these events reveal a lot of information about their future cash flows. However, the firm-specific return variation peaks at the time when information is first published.

Contrary to the above studies, Kelly (2014) argues that price synchronicity is a poor inverse measure of price informativeness because private information is not the only factor explaining low price synchronicity. Instead, the author finds that non-synchronized stocks have a lower level of institutional ownership and attract less analyst attention. This contradicts with the statement that price informativeness results from the actions of informed traders and analyst coverage. Private information is also incorporated into prices through risk arbitrage. However, Kelly (2014) shows that low-R^2 are smaller than high-R^2 stocks which means that they are also less frequently traded and therefore less liquid. Consequently, less synchronized stocks face higher trading costs, and they reveal more costly private information because of larger price reactions that are covered by less noise trades. This reduces the profits of information acquisition which is why low-R^2 stocks are not especially attractive for risk arbitrageurs. Thus, Kelly (2014) finds that private information is responsible for only 14% of the returns in less synchronized stocks. Synchronized stocks also experience private information events more often than their less synchronized equivalents. These results suggest that low price synchronicity is not solely explained by firm-specific information, but other common explanatory factors exist.

3 Asset pricing models

This chapter introduces the most relevant asset pricing models to provide basic insight into stock valuation. The market-based valuation models are founded on a modern portfolio theory that is presented at the beginning of this chapter. After that, the chapter moves on to the capital asset pricing model and the Fama-French three-factor model. These models assume that asset prices already include all available fundamental information, but investors rarely agree about the intrinsic value of a stock so market value might deviate significantly from the company's fundamentals. Thus, this chapter also introduces income-based discount models such as the dividend discount model and discounted free cash flow model which determine the fundamental value of a company by estimating its profitability in the future.

3.1 Modern portfolio theory

Market-based asset pricing models introduced in this chapter are based on Markowitz's portfolio optimization model (1952). This modern portfolio theory is based on the assumption that investors are risk-averse operators who pursue maximum expected return with minimal possible risk. Markowitz (1952) defines risk as a variance from expected returns. By diversifying funds among low-correlation assets, an investor can reduce portfolio risk and achieve an optimal risky portfolio that offers maximum expected return with minimum variance.

Security selection in Markowitz's (1952) model begins with identifying the minimum-variance frontier illustrated in Figure 1. The minimum-variance frontier includes all the risky asset portfolios with the least variance for a given expected return. Since investors can reduce the risk of a risky asset by diversifying, single risky assets are inefficient and therefore located on the right side of the frontier. The least risky global minimum variance portfolio is located at the very point of the frontier. Portfolios above the global minimum variance portfolio offer the best return-risk ratios. Thus, these are the only potential optimal portfolios and together they form the efficient frontier of risky assets.

Portfolios below the global minimum variance portfolio are inefficient. Next, the optimal risky portfolio is determined by fitting a tangent from a risk-free asset such as a Treasury bill to the efficient frontier. This tangent is referred to as the optimal capital allocation line (CAL) which has the steepest slope and therefore highest Sharpe ratio. Sharpe ratio measures the return-risk relationship and so the objective is to achieve the highest possible ratio. Finally, the investor will allocate investment between the optimal risky portfolio and the risk-free asset.

According to Tobin's (1958) separation property, defining the optimal risky portfolio and capital allocation are two separate tasks. The optimal risky portfolio is a technically obtained portfolio that is the same for each investor whereas capital allocation depends on the investor's personal risk preferences. For instance, a risk-averse investor weights more risk-free assets moving closer to the risk-free asset along the CAL.

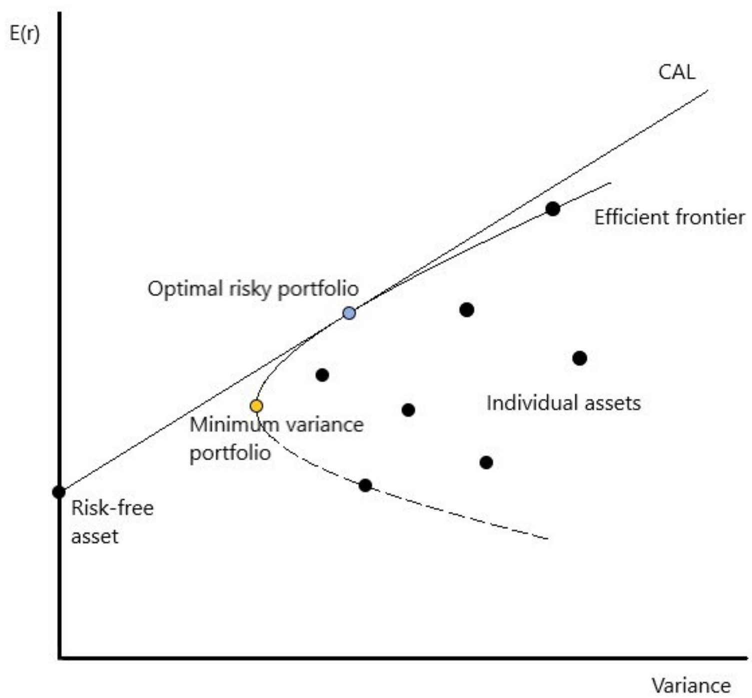

Figure 1. The efficient frontier of risky assets in the portfolio optimization model.

3.1.1 Capital asset pricing model

The capital asset pricing model (CAPM) introduced by Sharpe (1964), Lintner (1965) and Mossin (1966) assesses the relation between expected return and risk of an asset. The model is based on the assumption introduced in Markowitz's (1952) portfolio theory stating that investors aim for the optimal risky portfolio. However, the revolutionary remark in the CAPM is that since all investors would invest in the same optimal risky portfolio, regardless of their risk aversion, it must be a market portfolio. A market portfolio is the sum of all the risky portfolios of each investor, therefore including all the assets of the market weighted by their market value. In other words, a stock's weight is the same in each common risky portfolio and since the market portfolio is comprised of these portfolios, it too has the same weights. All assets are included in the market portfolio because if no one invests in a certain stock, its price will decline until it is too attractive to be excluded from the optimal risky portfolio. Consequently, optimal CAL becomes the capital market line (CML) in which M is the optimal market portfolio on the efficient frontier.

According to the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966), the risk premium of an individual security depends on its influence on the market portfolio's risk because portfolio risk is what matters to the investors. CAPM assumes that investors are rational, share similar expectations, can borrow or lend at a risk-free rate and that all assets are publicly traded. The risk premium of the market portfolio is determined by the average degree of investors' risk aversion and portfolio variance. The risk premium of an individual stock, on the other hand, is measured by its covariance with the market. This means that a stock with a negative covariance reduces the risk of the market portfolio and vice versa. The key insight of the model is that all securities should provide an equal return-risk ratio because otherwise, investors would shift their investments towards more rewarding assets. This means that all fairly priced securities should lie on the security market line (SML) or else the stock is mispriced. In efficient markets, these deviations are quickly corrected as investors exploit the mispricing until the security price adapts to its competitive level. Consequently, the authors establish the following standard CAPM equilibrium:

$$E(r_i) = r_f + \beta_i \left[E(r_M) - r_f\right] \tag{1}$$

In the model, the expected return of a security $E(r_i)$ is the sum of the return of the risk-free asset (r_f) and market risk premium $\left[E(r_M) - r_f\right]$ multiplied by the security beta (β_i). Beta describes the impact of a stock on the variance of the market portfolio in relation to the market variance. The expected return-beta relationship of the CAPM holds for individual stocks but also for an entire portfolio that combines these assets. In conclusion, stock prices already reflect the market consensus about a company's future prospects based on all available public information so it should be impossible to earn excess returns. Therefore, expected returns should be determined solely by the company's exposure to the market risk measured by company beta. This is why earning high returns in efficient markets requires bearing more risk. These expected returns represent the paid stock price related to the expected future cash flows.

3.1.2 Fama-French three-factor model

Fama and French (1993) introduce two additional firm characteristics that expose to systematic risk in their three-factor model. Systematic risk refers to market risk that applies to the whole market and therefore cannot be removed by diversifying investments. In addition to the company's exposure to the market index, Fama and French (1992) provide empirical evidence showing that firm size and book-to-market ratio are related to increased return variation. This is because small companies are more vulnerable in uncertain market conditions and high book-to-market companies tend to face financial distress more frequently. In other words, small companies and value stocks are more sensitive to market risk which is why small stock and value stock portfolios provide higher expected returns. Thus, the Fama and French (1993) three-factor model proposes the following regression:

$$R_i = \alpha_i + \beta_M R_M + \beta_{SMB} SMB + \beta_{HML} HML + \varepsilon_i \tag{2}$$

This equation states that the expected excess return $[R_i = E(r_i) - r_f]$ in the portfolio i results from the sum of its alpha (α_i), error term (ε_i) and sensitivity to excess market index return $[R_M = E(r_M) - r_f]$, size and book-to-market ratio. Here, beta addresses the portfolio's return sensitivity to the given factor. Small minus big (SMB) describes the difference in returns of small stock and large stock portfolios. High minus low (HML) measures the difference between the returns of high and low book-to-market stock portfolios. Alpha describes abnormal returns that cannot be explained by market risk premium and therefore alpha stocks do not lie on the SML. Instead, positive alpha stocks lie above SML meaning that they are underpriced and provide excess return without additional risk. Negative alpha stocks, on the other hand, are overpriced and lie below SML. Detecting positive and negative alphas generally requires superior information or security analysis. The error term is a residual variable that represents firm-specific surprises which cause scatter returns to deviate from the plot.

3.2 Income based valuation

The market-based asset pricing models rely on the Fama's (1970) efficient market assumption that stock prices already reflect fundamental information about the company's prospects and future incomes. However, investors may derive differing interpretations and forecasts from this information which is why pricing errors occur also in efficient markets (Fama, 1965). Yet, a constant search for mispriced securities furthers information acquisition and market efficiency. Income-based valuation models can be utilized in determining a company's intrinsic value according to its profitability now and in the future. These equity valuation models are generally used among fundamental analysts to assess the fair market value of a company based on its fundamental information found in financial data.

Financial statements capture the historical values of a company's assets and liabilities which is why book value is a straightforward but rather limited view of a company's worth. The book value of an asset refers to its original cost at the time it was purchased deducted with yearly depreciations while disregarding changes in its current market value. Moreover, not all companies include intangible assets such as expertise or branding referred to as goodwill in their financial statements. Hence, market values generally differ from actual book values.

According to Tobin's (1969) Q-theory, the relation between market value and replacement cost of assets approaches one over time. Replacement cost describes the amount of capital it would require a company to replace all its assets at current market prices. In practice, Tobin's Q is a ratio of a company's market value to the book value of its assets at replacement prices. According to the theory, the market value of a company cannot constantly exceed the replacement value because the threat of potential competitors should force the market price to its fair level. Thus, the market value of a company should eventually equal the value of its assets. Yet, historical data from the U.S. stock market shows that Tobin's Q-ratio can substantially differ from one even for long periods (Board of Governors of the Federal Reserve System, 2023).

3.2.1 Dividend discount model

Financial statements provide valuable information about the company's current book value but forecasting future earnings and dividends enables a more accurate estimation of a company's intrinsic value. Income-based models assume that investors' expected holding-period stock return consists of capital gains or losses and received dividend payments. According to the dividend discount model, the present value of a stock equals all its expected future dividends until perpetuity is discounted to the present. This is stated in the following equation:

$$P_0 = \sum_{t=1}^{T} \frac{D_t}{(1+r)^t} + \frac{TV}{(1+r)^t} \tag{3}$$

Here, the present value of a stock (P_0) is the sum of all the future dividends (D) discounted to the present according to the required rate of return on equity (r). The required rate of return depends on the riskiness of a company, also referred to as the market capitalization rate, and it is obtained from the CAPM introduced in the previous chapter. TV stands for a terminal value of a stock in which dividends grow at a constant rate (g) to perpetuity. This is generally known as the Gordon growth model (1959) and here it illustrates the present value of a growing perpetuity:

$$TV = \frac{D_0\,(1+g)}{r-g} = \frac{D_1}{r-g} \tag{4}$$

When the growth rate increases, the stock price increases. Also, the growth rate should be less than the market capitalization rate to obtain valid results.

3.2.2 Discounted free cash flow model

The application of the dividend discount model is quite limited because it can be applied only to companies that pay dividends on a regular basis. Moreover, Modigliani and Miller (1958; 1961) suggest that dividend policy nor capital structure should not affect the market value of a company. In the first proposal of their model, Modigliani and Miller (1958) argue that capital structure is irrelevant in defining the market value of a company because capital structure only reveals the debt-equity ratio that a company uses to finance its assets. A leveraged company uses debt in financing which is why its cash flows are distributed between equity and debt holders. However, companies create additional value only through their assets. How these assets are financed or how the generated cash flows are distributed makes no difference in a company's value. Therefore, the market value of a leveraged company should be the same as that of the unleveraged company or else an arbitrage opportunity would exist.

The discounted free cash flow model follows the same principle as the dividend discount model but it can be utilized also by the companies that make no dividend payments. Instead of dividend payments, the present value of a company is determined by discounting free cash flows at the weighted average cost of capital (WACC). WACC is the weighted average cost of debt (r_D) and equity (r_E) per year and it is obtained according to the following equation in which E stands for equity and D for debt:

$$WACC = r_D \frac{D}{E+D} + r_E \frac{E}{E+D} \quad (5)$$

In their second proposition, Modigliani and Miller (1958) show that indebtedness increases the riskiness of a stock because a leveraged company is more exposed to financial distress. Therefore, shareholders will demand a higher return on equity along with a growing debt-equity ratio and rising beta. However, the rise in expected returns is offset by the additional financial risk and after all WACC remains unchanged as capital weights shift towards cheaper debt financing. This means that WACC also remains unaffected by the capital structure.

The free cash flow (FCF) is the portion of cash flows from a company's operating activities that could be freely distributed to shareholders after taxes and investment activities:

$$FCF = EBIT - taxes + depreciation - capital\ expenditure - \Delta WC \quad (6)$$

Here, EBIT stands for earnings before interest and taxes whereas ΔWC equals a change in working capital compared to the previous year. Working capital is the difference between current assets and liabilities. It measures solvency which reveals how successfully a company finances its main operating activities. Finally, the present value of a company can be determined by discounting free cash flows by WACC as follows:

$$PV = PV_{FCF} - PV_D = \sum_{t=1}^{T} \frac{FCF_t}{(1+WACC)^t} + \frac{TV}{(1+WACC)^t} - D \quad (7)$$

Here, the company's present equity value (PV) is obtained when the present value of debt (PV_D) is deducted from the derived value of the company (PV_{FCF}). TV stands for the terminal value of the company when the cash flows continue to grow at a constant rate to infinity. TV is estimated using the Gordon growth model (1959) similarly as in the dividend model:

$$TV = \frac{FCF_0\,(1+g)}{WACC - g} \tag{8}$$

Nevertheless, both of the Modigliani and Miller (1958) propositions only apply in perfect market conditions where there are no taxes or bankruptcy costs. The theory also assumes that companies make no investments and that all the profits are fully distributed to the shareholders. However, capital structure does matter in reality where companies face taxes and bankruptcy costs in most business environments. A leveraged firm can save in tax payments by utilizing a tax shield. Financial expenses are generally deductible from taxable income and by contracting debt financing company can increase its earnings. As Modigliani and Miller (1958) consider taxes in the model, the enterprise value will increase by the present value of its tax shield that is interest payments multiplied by the tax rate discounted by the cost of debt.

4 Literature review

This chapter provides comprehensive overall insight into how prevailing HFT literature views HFTs as new market intermediaries and their controversial effects on market efficiency from short and long-term perspectives. First, this chapter presents how HFTs behave as informed traders, introducing the most common HFT strategies and how HFTs differ from traditional market makers. Then proceeding on how HFTs enhance short-term price discovery by predicting near price changes, trading toward permanent price movements, and increasing liquidity while reducing spreads, transaction costs, and market underreaction. Next, the chapter goes through conflicting views on how HFT contributes to volatility and systematic risk. Finally, the chapter introduces a yet scarce selection of studies suggesting that HFT potentially hampers long-term price informativeness as short-lived HFT speculation, manipulative strategies and dark pools hinder the acquisition of new fundamental information.

4.1 HFTs as informed traders

Hasbrouck and Saar (2013) divide algorithmic trading into proprietary and agency activities from which HFTs represent a subset of proprietary algorithms. The buying institutions and the brokers in their service utilize agency algorithms to minimize trading costs as they adjust their trading portfolios according to prevailing market conditions and their followed strategies (Hasbrouck & Saar, 2013). The main purpose of these algorithms is to execute a certain position change at minimum transaction costs by splitting large orders into smaller trades that are sent to several different exchanges for execution. These algorithms monitor multiple venues over time and make decisions based on the results of historical price impacts and execution probabilities. They rarely require present information, except for their executing orders. Institutions do not necessarily need millisecond responses to react to market changes and since they aim to achieve a certain position, they generally implement liquidity-demanding market or limit orders (Hasbrouck & Saar, 2013).

Proprietary algorithms, on the other hand, include more variety in their behaviour (Hasbrouck & Saar, 2013). However, a recognizable feature in proprietary algorithms used in HFT is the extremely high speed that is achieved with co-location and low latencies. Speed is vital for these algorithms because instead of profiting from stocks or other securities they pursue profit from trading venues by providing liquidity or detecting statistical arbitrage opportunities (Hasbrouck & Saar, 2013). The presence of agency algorithms forces proprietary algorithms to provide rapid millisecond responses to market changes. Proprietary algorithms form so-called strategic runs to get ahead of the book. These runs are part of their followed strategy including order submissions, cancellations, and executions to react to market events. For example, if the bid in the limit order book improves, potential sellers compete to close it whereas other buyers adjust their bids to stay competitive and keep their place in time priority order. So, the algorithms race against each other as they share a common ambition to execute orders optimally and get on the top of the book. The millisecond timeframe between order submissions and cancellations indicates that these activities are not meant to signal humans who are unable to observe changes in such frequencies. Instead, Hasbrouck and Saar (2013) suggest that algorithms try to interact with each other by triggering a response from other algorithms with their actions.

4.1.1 The various strategies of HFTs

HFTs follow various strategies that may have diverging contributions to market efficiency. HFTs cannot be treated as one homogenous group of traders since there is significant heterogeneity between HFTs and their trading patterns (Benos & Sagade, 2016; Zhang, 2018). Over an hour-long horizon, all HFTs are mean-reverting and follow very similar patterns of correlation (Benos & Sagade, 2016). However, in short horizons measured in seconds, HFTs follow different trading strategies according to which Benos and Sagade (2016) divide HFTs into three different groups: aggressive, neutral, and passive HFTs. Aggressive HFTs are the most informed group of HFTs. They usually rely on news announcements or statistical arbitrage strategies consuming liquidity in their trading. Consequently, aggressive HFTs trade towards permanent price movements whereas neutral

HFTs act on trends and trade in the direction of transitory price changes. Passive HFTs, on the other hand, act like market makers as they supply liquidity by submitting limit orders. HFT market makers' liquidity-providing orders cover around 60-70% of the whole HFT trading volume indicating that most HFTs operate as passive market makers who provide liquidity to the markets (Hagströmer & Nordén, 2013). In addition, passive HFTs have higher order-to-trade ratios than aggressive HFTs, meaning that a smaller share of their orders are executed.

HFTs' effects on price discovery differ depending on their followed strategies (Benos & Sagade, 2016; Zhang, 2018). Brogaard et al. (2014) show that overall HFTs trade in line with future price changes. However, this results from aggressive liquidity demanding HFT trades while liquidity supplying HFTs are positively correlated with pricing errors. Benos & Sagade (2016) consistently find that aggressive HFTs trade towards permanent price movements whereas the contribution of neutral and passive HFTs is either opposite or insignificant (Benos & Sagade, 2016). These results indicate that aggressive HFTs have the most significant effect on price discovery. More precisely, Benos and Sagade (2016) show that 14% of the total trade-related information is contributed by HFTs of which 10% is produced by aggressive HFTs and the remaining 4% by neutral and passive HFTs.

4.1.2 HFTs versus traditional market makers

HFTs have proved their place as a new type of market intermediaries. They differ from traditional market makers with their sophisticated algorithms that provide superior advantages in information processing and order submission. Furthermore, HFT market makers have high order-to-trade ratios and low latencies which represent their role as today's modern market makers who react instantly to news announcements and order flows by submitting and modifying orders (Hagströmer & Nordén, 2013). The traditional market makers and HFTs also have some common features: they both have short holding periods, and they trade frequently (Brogaard et al., 2014). However, HFTs do not have the same obligations or corresponding privileges as traditional market makers. Traditional market makers have privileged access to the markets that are unavailable to other participants so they must fulfil certain assigned obligations (Brogaard et al., 2014). These obligations require that market makers always supply liquidity regardless of the prevailing market conditions while they are also constrained from demanding liquidity.

Limiting market makers from demanding liquidity reduces the adverse selection costs which they may cause to other investors with their enhanced reaction ability to news announcements and possessing inclusive information about the order flow (Brogaard et al., 2014). Since HFTs are not obligated with such duties, they can follow strategies that are not possible for traditional market makers. Because HFTs are not constrained from demanding liquidity, they may impose non-HFTs to more adverse selection costs while exploiting their speed advantage to gain an informational edge. However, Menkveld (2013) detects that 80% of the HFT market makers' trades are liquidity-supplying passive limit orders. Moreover, Brogaard et al. (2014) find supporting results indicating that HFT market makers stay consistent in providing liquidity even in times of high volatility. Like any other liquidity suppliers, HFTs are also adversely selected when supplying liquidity, but less so because they are more successful in avoiding adverse selection costs than non-HFTs (Brogaard et al., 2014; Carrion, 2013; Zhang, 2018). This can be explained by the slower response of non-HFTs during an information shock whereas HFTs can quickly change their position (Zhang, 2018).

4.2 HFT enhancing price discovery

Most of the recent academic research supports that HFT improves short-term market efficiency by enhancing price discovery and information incorporation into prices (see e.g., Brogaard et al., 2014; Carrion, 2013; Chordia & Miao, 2020; Ke & Zhang, 2020). HFTs' superior speed in information processing benefits the price discovery process but also exposes other market participants to adverse selection costs. Zhang (2018) examines price discovery between futures and stock markets finding that HFTs are able to process hard quantitative information quicker than non-HFTs and tend to trade more aggressively according to this information. The study focuses on HFT index arbitrage strategies that search mispricings between an index and its components. Zhang (2018) shows that

HFTs' superior advantage in information processing helps them to react faster to hard information than non-HFTs. However, the author notes that even though the study focuses mainly on the HFT index arbitrage strategies which are some of the most applied HFT strategies, the results do not necessarily apply to all strategies used in HFT.

During an information shock, liquidity demanding HFTs first trade in the direction of hard information but after a few seconds, HFTs reverse their trading and start selling off their position (Zhang, 2018). This is done to gain profit as a part of their arbitrage strategy. HFTs use futures market information in their trading at stock markets, and by doing so, they reduce the information delay between these markets. So, HFTs enhance information mobility from the futures markets causing information to be incorporated into stock prices more efficiently (Zhang, 2018). This results in faster price adjustment and improved price efficiency in stock markets.

Moreover, HFTs exploit multiple other sources of information in their trading. HFTs use macroeconomic news announcements, market-wide returns or limit order book imbalances to predict near price changes (Brogaard et al., 2014). Carrion's (2013) research consistently suggests that a higher level of HFT positively correlates with faster information incorporation from order flow and market index returns. These results consequence of HFTs' liquidity-demanding activities. Furthermore, HFT reduces post-earnings announcement drift (PEAD) which indicates quicker price adjustment after public announcements (Chordia & Miao, 2020; Ke & Zhang, 2020). This supports the view that HFT incorporates information more sufficiently into prices.

4.2.1 Ability to predict near price changes

With the help of superior advantage in information processing and speed, HFTs can obtain and utilize information before the rest of the market. Therefore, HFTs can predict short-horizon price changes that occur in timeframes of a few seconds (Brogaard et al., 2014). These findings are consistent with the results of Aït-Sahalia and Brunetti (2020) showing that HFTs have a high success rate on each transaction. This can be observed from the forthcoming price changes that are likely to move in the direction of HFTs' predictions but also from the shorter time periods during which HFTs realize their profits. However, HFTs' winning rate is remarkably higher only when they trade against non-HFTs. HFTs lose their superior advantages when they trade against each other which is why they try to avoid other HFTs as counterparties (Aït-Sahalia & Brunetti, 2020).

Brogaard et al. (2014) find that HFTs' liquidity demand in one second, forecasts the later liquidity demand of other traders. This indicates that HFTs can predict the liquidity demand of non-HFTs. The trades of traditional investors include information about expected returns which is why HFTs' predictive liquidity demand fosters the incorporation of this information into stock prices (Brogaard et al., 2014). Moreover, their high success rate in predicting price changes includes both transitory and permanent price movements from which pricing errors become eliminated and new information becomes incorporated into prices. This helps markets to reach more informative prices and reduces noise in the price process (Brogaard et al., 2014). Carrion (2013) comes to a similar conclusion stating that HFTs contribute to more efficient prices while pursuing profits from successful market timing. A high success rate in market timing indicates that there is predictability in intraday stock prices which equals inefficiency according to efficient market theory. However, regardless of intraday inefficiencies, markets can remain efficient in long-term as long as predictability is short-lived and scarce in the markets (Chordia et al., 2008; Malkiel 2003). Consistently with these findings, Malkiel (2003) expects prices to become increasingly more predictable in the future as development in statistical technologies helps detect correlations more efficiently.

As introduced in the previous chapter, HFTs capitalize on macroeconomic news announcements and limit order imbalances in their trading. More accurately, they use these sources of public information and market-wide returns to predict near price changes (Brogaard et al., 2014). Liquidity demanding HFTs trade in the direction of the news announcements meaning that they buy when positive news is announced and sell when negative news is announced. Liquidity supplying HFTs, on the contrary, trade in the opposite direction. However, Brogaard et al. (2014) find that liquidity supplying HFTs' proportion is larger and thus the overall direction of HFT trading is against macroeconomic news. The authors conclude that HFTs serve as active liquidity providers also during macroeconomic announcements which often involve uncertainty. Brogaard et al. (2014) and Cao et al. (2009) show that HFTs also use limit order information to predict upcoming price changes. According to Brogaard et al. (2014), liquidity demanding HFTs trade in the direction of the book imbalance, meaning that they buy when there are many other buyers but not as many sell orders. Liquidity supplying HFTs, on the other hand, supply liquidity to the thinner side of the book. However, liquidity demanding HFTs exploit the limit order book more aggressively than liquidity supplying HFTs which shifts overall HFT trade toward the thin side of the book (Brogaard et al., 2014).

4.2.2 Trading towards permanent price movements

Informed HFTs enhance price efficiency by trading in line with permanent price movements and in the opposite direction from transitory pricing errors. Brogaard et al. (2014) divide price changes into permanent and transitory components. The permanent component refers to information whereas the transitory component equals pricing errors, volatility, or noise. HFTs' followed strategies determine whether their trading takes direction towards permanent price movements or transitory pricing errors. According to Brogaard et al. (2014), HFTs' liquidity supplying limit orders are adversely selected and associated with pricing errors if they are associated with predatory trading, price manipulation or risk management. HFTs' liquidity demanding orders, on the other hand, are aligned with permanent price movements as these are related to arbitrage strategies that capitalize on informational advantage by overcoming the bid-ask spread and trading fees.

Nevertheless, Brogaard et al. (2014) observe that beneficial HFT activities are yet more dominant than detrimental strategies. Thus, HFTs improve price efficiency by trading in the direction of permanent price changes and by reducing intraday pricing errors. However, these short-term improvements in price efficiency do not necessarily equal more sufficient asset allocation or investment decisions in longer horizons (Brogaard et al., 2014). According to the efficient market theory, these improvements in information incorporation and reduction in pricing errors enhance market efficiency because prices adjust faster and more accurately to new information. However, the superior advantage in information processing offers HFTs the ability to be more informed than other traders, creating information asymmetry in the market as discussed in Chapter Two. So, while HFTs demand liquidity according to this informational edge, HFTs end up imposing adverse selection costs to other investors in the market (Brogaard et al., 2014; Brogaard et al., 2017). However, adverse selection is observed to have a relatively small impact on price discovery and it eventually evens out by the positive outcomes of improved price efficiency (Brogaard et al., 2014; Brogaard et al., 2019).

4.2.3 Improved liquidity and narrower spreads

Bid-ask spread illustrates the price gap between the highest buy order and the lowest sell order. Liquidity providing market makers generally earn the spread while liquidity consuming aggressive traders pay the spread (Hagströmer & Nordén, 2013). When bid-ask spread is narrow, buy and sell orders are more likely to match leading to the execution of the orders. Thus, spread indicates the level of liquidity but also determines transaction costs.

Several studies share the common view that HFT increases market liquidity (Brogaard et al., 2014; Carrion, 2013; Hasbrouck & Saar, 2013; Hendershott et al., 2011). Hendershott et al. (2011) find that an increase in algorithmic trading leads to more liquid markets. According to the authors, AT mitigates the need for human intervention as advanced technology and automation reduce trading costs and make market quotes more informative. Since non-HFTs face relatively high monitoring costs, their limit orders do not always reflect all public information. HFTs, on the other hand, can adjust their orders constantly due to algorithmic monitoring and efficient order submission with zero marginal costs. However, Hendershott et al. (2011) note that their five-year observation period coincides with economic upswing, so it is unclear whether HFTs improve liquidity during market uncertainty.

Hendershott et al. (2011) also detect narrower quoted and effective spreads, especially in large-cap stocks. This either results from the decrease in adverse selection or price discovery related to trades. Reduced trade-related price discovery means that more price discovery is realised without trading, indicating that submitted quotes have become more informative than before (Hendershott et al., 2011). Carrion (2013) consistently suggests that HFT liquidity supply narrows spreads since liquidity supplying HFTs are able to avoid adverse selection costs better than non-HFT liquidity suppliers. Moreover, the author finds that HFTs provide liquidity for wide-spread stocks while demanding liquidity from narrow-spread stocks. This shows that HFTs supply liquidity when it is needed and demand liquidity when there is plenty.

Brogaard et al. (2014) show that HFTs continue actively supplying liquidity in volatile market conditions and around macroeconomic news announcements. However, the problem is that even though HFTs keep supplying liquidity actively even in times of uncertainty, their imposed adverse selection costs may repel other liquidity suppliers causing market instability (Brogaard et al., 2014). The later study of Brogaard et al. (2017) supports this claim as the authors find that some of the HFT activities are harmful to market liquidity during volatile market conditions. The authors study HFTs' short selling impacts on liquidity during the short-sale ban in 2008. The short-sale ban was implemented by the SEC to forbid most of the short selling activities due to the high volatility of the time. Brogaard et al. (2017) find causal evidence indicating that a rise in HFT short selling increases spreads and reduces liquidity. This is because HFT short selling causes additional adverse selection to other liquidity suppliers and erodes the competition among liquidity providers. However, the authors note that the adverse selection caused by HFTs could have been exceptionally high because of the prevailing uncertainty during that time. Non-HFT short selling on the contrary increases liquidity and decreases spreads. There is also a notable difference between short selling HFTs and HFTs that do not use short selling strategies (Brogaard et al., 2017). In fact, HFT liquidity demand from non-HFTs that do not sell short could even benefit the overall market liquidity accounting that non-HFTs' short selling improves liquidity.

In conclusion, HFTs provide necessary liquidity to the markets even in times of uncertainty. Higher liquidity and thus lower liquidity costs increase arbitrage activities and enhance the incorporation of private information into stock prices (Chordia et al., 2008). Orders are also executed faster, and investors can trade on smaller pieces of information when there is more liquidity available. Thus, stock returns become less predictable, and prices resemble more closely random walk in liquid market conditions where spreads are narrow (Chordia et al., 2008). In other words, enhanced liquidity leads to more efficient market conditions and improved price informativeness. However, HFT liquidity supply and their short selling activities can be detrimental to market liquidity during high volatility as they repel other liquidity suppliers causing excess market instability.

4.2.4 Lower transaction costs

The decline in human intervention leads to narrower spreads and consequently lower trading costs (Hendershott et al., 2011). HFTs as new market intermediaries exploit algorithms to analyse various securities and trading venues simultaneously as the algorithm chooses the timing, price, quantity, and routing of orders (Hendershott et al., 2011). Liquidity suppliers face adverse selection costs when trading with more informed traders like HFTs, and effective spreads exist to compensate these costs to market makers who earn the spread (Carrion, 2013). Effective spread measures the gap between the execution price and the pre-trade midpoint. The spread also includes compensation from carried inventory risk, order processing costs and market-maker rents.

However, Carrion (2013) finds that mean realized spreads are negative. This indicates that effective spreads do not completely compensate for the adverse selection costs imposed by informed traders. Liquidity supply does not necessarily become unprofitable as market makers keep receiving liquidity fees, but the compensation for liquidity provision declines significantly (Carrion, 2013). According to the author, such a decline in liquidity provisions can arise from increased competition or development in submission strategies. Brogaard et al. (2014) consistently suggest that HFTs compete for attractive trading opportunities and based on their HFT revenue analysis, HFT returns are relatively thin compared to their trading volume. This potentially indicates that HFT behaviour leads to more competitive market conditions. Carrion (2013) and Hendershott et al. (2011) both support this statement by showing that HFT presence contributes to more intense competition in liquidity supply. Increased competition drives liquidity compensations down which again lowers transaction costs in the market.

Although Carrion's (2013) results indicate that HFT participation could explain lower trading costs, the author cannot ensure the causality between these two. In fact, it is quite likely that the causality runs in the opposite direction meaning that HFTs deliberately choose to trade stocks with lower expected trading costs. Either way, HFT presence alone can reduce trading costs in the market even when they would not take an active part in the particular trade (Carrion, 2013). This is because the presence of HFTs leads to more intense competition and mitigated adverse selection. HFT short selling, on the contrary, has the opposite impact. Some rare detrimental strategies of HFTs such as predatory trading also have the opposite effect as they trade towards pricing errors and therefore increase transaction costs (Manahov et al., 2014). Overall, lower transaction costs enhance price informativeness by encouraging more informed trading and incorporating more fundamental information into prices (Chordia et al., 2008; Chordia & Miao, 2020).

4.2.5 Reduced market underreaction

Fundamental information is vital for traditional investors with long investing horizons. Ke and Zhang (2020) argue that corporate earnings news is the most relevant form of fundamental information. Therefore, they examine market underreaction to earnings news to find out how HFT affects informational efficiency. The authors measure market underreaction by the magnitude of post-earnings announcement drift (PEAD). PEAD indicates the level of investors' underreaction to earnings news announcements instead of reacting quickly and fully to the news (Ke & Zhang, 2020). This causes stock prices to slowly drift to their correct level as opposed to immediate adjustment. PEAD arises from limited investor attention during news announcements and high transaction costs which mitigate the profitability of informed arbitrage trading (Hirshleifer et al., 2009; Ng et al., 2008). Ke and Zhang (2020) show that HFT reduces PEAD because it decreases transaction costs and offers investors facilities for broader attention.

Chordia and Miao (2020) find supporting evidence indicating that an increase in HFT activity lowers PEAD. They notice that aggressive HFT during earnings news announcements results in faster and more accurate incorporation of earnings surprises into stock prices while reducing the drift. Ke and Zhang (2020) achieve similar results and additionally, they discover that the effect is stronger when earnings surprises are significant and extreme. The authors also specify that a decrease in PEAD results from the HFT liquidity supply. This implicates that the increase in HFTs' liquidity supplying activities reduces market inefficiencies that are relevant also at longer horizons.

Chordia and Miao (2020) find contrary that both liquidity supplying and demanding HFTs trade in the direction of the earnings surprise. They argue that both activities lead to a stronger price effect during the earnings news announcements and therefore reduce PEAD. More importantly, the observed reduction in PEAD and the following positive contributions to market efficiency could persist for up to a year. This can be considered meaningful also to long-term investors. Chordia and Miao (2020) also find that HFTs enhance the incorporation of news related to inside trading as well as merger and acquisition announcements into prices more efficiently. However, HFTs tend to be most active in large and liquid stocks raising the possibility of reverse causality which would mean that HFTs intentionally trade stocks with more informative prices (Chordia & Miao, 2020).

Although, Chordia and Miao (2020) show a significant positive correlation between HFT and market efficiency, Erhard and Sloan (2020) challenge the missing causality behind their conclusions. The authors find results surprising since it is not distinct how millisecond improvements in trading speed could mitigate long-term mispricing. Instead, Erhard and Sloan (2020) suggest an alternative explanation for enhanced liquidity and long-term price efficiency – advanced market microstructure. However, the authors are consistent with Chordia and Miao (2020) and Hendershott (2011) pointing out that much like HFTs, these microstructure developments only enhance the efficiency of large and already liquid stocks while small illiquid stocks remain unaffected.

4.3 Volatility and systematic risk

Volatility describes a standard deviation from expected returns. High volatility reflects increased risk because of the greater likelihood of realized returns to differ from expected returns. Therefore, excess volatility equals uncertainty that is generally undesirable for investors and causes inefficiencies in the market (Carrion, 2013). Shiller (1981) provides empirical evidence indicating that stock prices are too volatile to represent only expected returns and the random arrival of new fundamental information. In the worst-case scenario, excessive volatility can lead to market failure which can prolong a long-lasting recession. According to Lim et al. (2008), financial crises lead to inefficiencies in the markets because investors tend to panic when there are signs of a slump. General hysteria disturbs efficient market pricing as prices overreact to new information while the amount of news and market rumours increase significantly in stressful market conditions. This is consistent with studies suggesting that stock prices tend to over-react on news and HFT seems to reinforce this effect (Malkiel 2003; Zhang, 2010). Eventually, improvements in market efficiency help markets to recover from recession over the post-crisis period (Lim et al., 2008).

The research field appears divided when it comes to HFT and market volatility. The common concern is that HFT raises volatility or at least contributes to the negative effects of market stability (Brogaard et al., 2019; Jain et al., 2016; Zhang, 2010). Zhang (2010) finds a positive correlation between stock price volatility and HFT as one standard deviation increase of HFT grows stock volatility by 5,6%. The effect is stronger for the largest 3 000 public companies in the U.S. market, stocks with significant institutional holdings, and under uncertain market conditions. Zhang (2010) states that HFTs lead stocks to overreact to fundamental news which reinforces price instability.

Contrary to the general view, some studies show evidence that HFTs do not accelerate market volatility and could even mitigate short-term price fluctuations (Aït-Sahalia & Brunetti, 2020; Hagströmer & Nordén, 2013; Hasbrouck & Saar, 2013). Hasbrouck and Saar (2013) find that HFTs decline short-term volatility and suggest that in volatile market conditions, small low-volume stocks that are usually unattractive to HFTs may turn into profitable trading opportunities. Hagströmer and Nordén (2013) even manage to show causality between liquidity providing HFTs and mitigated short-term volatility. However, this finding applies solely to market making HFT activities since the authors are unable to show causality between aggressive HFTs and volatility. Brogaard et al. (2014) do not provide direct evidence on how HFTs affect market stability, but they show that HFTs keep trading against transitory pricing errors and providing liquidity even in volatile times. Aït-Sahalia and Brunetti (2020) find supporting results indicating that HFT liquidity supply mostly remains stable in volatile conditions, although it declines during extreme volatility.

Even though HFT presence does not necessarily increase volatility and they would stay consistent with liquidity supply, a sudden market slump in 2010 known as the Flash crash has gathered long-lasting negative attention towards HFTs. Those events have raised concerns that Hasbrouck and Saar (2013) admit existing since there is a possibility that HFTs accelerate market failure during times of severe market uncertainty. As illustrated in the previous chapters, HFTs impose additional adverse selection costs on other liquidity suppliers causing them to withdraw from the market. This may exacerbate market instability during volatility if liquidity suppliers vanish when they are most needed (Aït-Sahalia & Brunetti, 2020; Brogaard et al., 2014). This can lead to a self-reinforcing phenomenon and potentially contribute to more uncertain conditions as reduced liquidity adds market stress and volatility (Aït-Sahalia & Brunetti, 2020).

Moreover, some later studies introduce issues concerning how increased volatility changes HFT behaviour. Usually, HFTs submit more limit orders than market orders, but Brogaard et al. (2019) discover that HFTs cut back liquidity providing limit orders and switch to liquidity consuming market orders during high volatility. This shift in HFT behaviour potentially reinforces the volatility impact as market orders involve private information and adverse selection which may further market uncertainty and expose to possible market failure (Brogaard et al., 2019). Aït-Sahalia and Brunetti (2020) on the contrary suggest that a surge in volatility and extreme price jumps cause HFTs to reduce their trading activities because the majority of their strategies aim to profit from small price movements instead of large jumps. So, the presence of HFTs does not necessarily create abnormal volatility, but their withdrawal from the market does.

Jain et al. (2016) examine the implications of HFT's entrance to the market and find that HFT increases systematic risk. According to the authors, there is not much research concerning whether HFTs cause greater losses due to episodic illiquidity resulting from the rise in systematic risk. Therefore, they study volatile market conditions where systematic risk most likely occurs. Jain et al. (2016) find that HFTs grow autocorrelation and cross-correlation of the order flow exposing markets to higher systematic risk. Systematic risk related to HFT seems to consequence of their liquidity demanding trades whereas high-frequency quoting imposes systematic risk when liquidity supplying quotes are extinct or withdrawn. In their analysis, Jain et al. (2016) compare their Tokyo Stock Exchange (TSE) stock results to Osaka Stock Exchange (OSE) stocks to find out that the systematic risk in the OSE control sample remains unchanged. This indicates that the observed increase in systematic risk in TSE stocks results particularly from HFT instead of general advancement in macroeconomic conditions. Although the main emphasis of the research is on the Japanese market, the authors find consistency in the market quality effects of HFT in the U.S. market, therefore suggesting that results apply to other markets as well.

In conclusion, HFT liquidity supply mitigates short-term market volatility, but in the meanwhile HFTs may accelerate volatility impact as they repel other liquidity suppliers and potentially switch to liquidity demanding market orders or reduce trading during high volatility. High volatility causes insecurity among investors and therefore exposes markets more likely to failures. During crises, hysterical market behaviour leads stock prices to overreact to news announcements which has detrimental effects on price informativeness and overall market stability.

4.4 HFT hindering information acquisition

Some HFTs are involved with detrimental strategies that use algorithms and private information to front-run other investors (Chordia & Miao, 2020). Front-running is a misconduct in which a trader uses private information, for example customer order information about a large buy or sell, to trade against the unexecuted order for their personal gain from upcoming price movements. These actions discourage investors from seeking new information as information acquisition becomes less profitable. This could result in the disappearance of informed traders leading to less informative prices regarding company fundamentals (Chordia & Miao, 2020). Weller (2018) obtains similar results indicating that AT has a remarkable negative impact on information acquisition reducing price informativeness by 9–13% per standard deviation. HFT is a subset of AT so this thesis relies on the assumption that these results apply to HFT as well. More accurately, the author shows that AT leads to a conflict between acquiring new information and incorporating existing information into prices. While AT improves the price discovery of already existing information, it also diminishes the acquisition of new information (Weller, 2018).

Companies and households build social welfare by making productive investment decisions and thus information acquisition is socially valuable only when it has an impact on these decisions (Weller, 2018). However, millisecond price adjustments are irrelevant in determining such decisions. Weller (2018) notes that most of the previous HFT studies focus solely on the increased market efficiency of already existing public information.

However, the research concerning HFTs' implications on price informativeness that results from information acquisition is largely missing. Weller (2018) uses the price jump ratio to measure relative information acquisition. The price jump ratio is the relation between the returns during the reveal of the information and the total return over the pre-announcement period. A high price jump ratio indicates a large impact of an announcement and reveals information that was not yet discovered or expected in the markets (Weller, 2018). Weller (2018) finds a strong positive association between AT and price jump measure meaning that less information acquisition was conducted before the announcement due to more active trading of HFTs. These results are consistent with the theory by Froot et al. (1992) suggesting that short-term speculators such as HFTs tend to rely on already existing information instead of acquiring new information.

Lee and Watts (2021) find similar results as they examine HFT's implications in the special setting of the Tick Size Pilot program. The authors detect that increased tick size reduces AT activity while observing a smaller price reaction to earnings announcements. This is shown in a sharp decline in absolute cumulative abnormal returns (ACARs) up to thirty days post-announcement period. However, a positive development in SUEs indicates that prices already reflect information about an upcoming earnings announcement suggesting improved information acquisition before announcement rather than reduced price discovery post announcement. This positive effect is observed up till three months before the announcement. Meanwhile, post-announcement price discovery remains as sufficient as before since Lee and Watts (2021) find no increase in PEAD. Findings of increased EDGAR search volumes and declined price synchronicity consistently support the conclusion of improved price informativeness pre-announcement period. Even though the authors are unable to show causality between AT and declined information acquisition, the results at least question the HFTs' effects on information acquisition consistently with Weller's (2018) findings.

In conclusion, Weller (2018) finds that HFT significantly reduces pre-announcement information acquisition. Furthermore, the author shows that the difference in the information content of HFT and non-HFT stocks grows when the moment of an announcement comes closer. HFTs or other ATs usually improve price efficiency by seconds or minutes after the news announcement but the detrimental effects of diminished information acquisition may occur even a month-long period before the announcement (Weller, 2018). Reduced information acquisition results in less informative prices and more severe pricing errors. Mispricings may have serious negative effects on general welfare if price uncertainty escalates to increased systematic risk or if noise costs lead to inefficient capital allocation (Weller, 2018).

Consistently, Gider et al. (2019) show that reduced information acquisition has even more far-reaching effects on price informativeness. They find that stock prices become weaker estimates of the company's future prospects after HFT entrance. The negative influence amplifies along with the growing forecasting horizon as stock prices become less accurate predictions of expected future earnings up to two-to-five-year forecasting horizons. According to their results, HFTs' ability to predict near price changes and upcoming order flow increases the transaction costs for institutional investors. Consequently, institutional investors reduce their active holdings and trades due to the declined profitability of information acquisition. This eventually leads to fundamentally less informed stock prices as institutional investors more frequently settle for tracking market portfolios instead of acquiring new distinctive information about potential investment opportunities.

4.4.1 The short-lived nature of HFT speculation

A theory by Froot et al. (1992) shows that speculators with short time horizons may hamper the informational quality of asset prices. Informed speculation models generally suggest that traders trade with long horizons and seek information that other participants are yet missing. However, Froot et al. (1992) suggest that speculators who operate in short horizons may herd on the same information that is already possessed by other informed traders and there is no guarantee that this information is related to fundamentals. In other words, these speculators seem to rely on the existing information of other traders instead of acquiring new information by themselves. Moreover, traders with shorter horizons do not necessarily use their research resources most optimally. Unlike typical models of informed trading, Froot et al. (1992) rely on positive informational spill-overs in which returns of early informed traders increase when a particular information spreads among other traders. Consequently, the authors note that speculators may excessively herd on certain information while choosing to ignore other types of information such as fundamentals. This hampers the informational efficiency of stock prices, eventually leading to the misallocation of resources.

The main purpose of financial markets is to allocate funds to the most productive parties of society and therefore markets need to reflect the true values of investments to produce maximum social welfare. Manahov et al. (2014) note that the short-lived nature of HFT trading potentially limits the social benefits since HFTs are generally more focused on the price changes in the next few seconds instead of the fundamental values of stocks. Ke and Zhang (2020) provide similar results suggesting that most of the HFT strategies are based on short-term statistical correlations of stock returns which do not necessarily serve stocks for investment purposes nor incorporate fundamental information into prices. Brogaard et al. (2014) also find evidence supporting these claims as they discover that HFT positively correlates with subsequent returns for only a short fraction of time. This remarkable correlation between HFT trades and stock returns at one second disappears rapidly as the correlation approaches zero after only two seconds (Brogaard et al., 2014).

4.4.2 HFT scalpers and market manipulation

Baldauf and Mollner (2020) study the core reason behind declined information acquisition shown in the previous studies: the trade-off between thinner spreads and reduced information production. This trade-off is generated from HFTs' order flow screening behaviour and superior speed which enables them to foreshadow traditional investors' orders. Thus, informed traders cut back their fundamental research as it becomes less profitable. HFT liquidity supply tapers bid-ask spreads due to reductions in informational asymmetries and adverse selection. After all, both aggressive and passive HFTs diminish the incentives of information acquisition (Baldauf & Mollner, 2020).

Manahov (2016) creates an artificial stock market environment to simulate the behaviour of predatory HFT scalpers and to examine their effects on long-term investors and market quality. The author discovers that HFT scalpers front-run order flow and tend to cancel a massive number of orders in short periods of time. The idea behind HFT scalping strategies is to gain the best possible position in the order line (Manahov, 2016). Scalpers seek supply and demand imbalances in the market depth so that they can step ahead of these orders to capture a microspread (Manahov, 2016). Predatory HFTs try to flood the market with the help of quote stuffing which means submitting and cancelling a significant number of orders in a way that enables them to step ahead of institutional order flows. This causes non-HFTs' orders to fall back in the limit order book breaking the price-time priority and hampering the execution of their orders. Order cancellation also raises trading costs and disturbs the trading of traditional long-term investors by inducing more uncertainty in order execution and therefore causing more transient prices (Manahov, 2016). Furthermore, order cancellation exposes market makers to increased adverse selection to which they respond by demanding wider bid-ask spreads.

Institutional investors such as pension funds for example can experience difficulties in executing large orders since HFTs can detect and front-run them (Manahov et al., 2014). Difficulties in order execution cause institutional traders to withdraw from the market and some of the traditional traders may even shift their trading into dark pools (Manahov, 2016; Manahov et al., 2014). Overall, scalping strategies potentially raise systematic risk and cause institutional traders to withdraw from the market mitigating the incorporation of fundamental information into stock prices (Manahov, 2016). Nonetheless, Brogaard et al. (2014) suggest that HFTs are rarely related to price manipulative activities shown by the negative association of HFT orders with pricing errors. In their later study, Brogaard et al. (2019) find that only a small fraction of HFTs conduct these aggressive front-running strategies and such behaviour does not represent the majority of HFTs.

4.4.3 HFT drives trading into dark pools

Front-running and other predatory HFT strategies have pushed institutional and traditional investors to relocate their orders into dark pools (Manahov et al., 2014). In 2009, there were approximately 32 dark pools that altogether covered 8% of the entire trading volume in U.S. securities exchanges (SEC, 2010). Manahov et al. (2014) describe dark pools as off-exchange trading venues where financial instruments are traded anonymously and orders are not displayed publicly so that prices remain hidden until execution. Trading shifting into dark pools causes negative outcomes for social welfare and long-term investors because it diminishes market transparency and increases expenses by imposing price obstacles for other investors (Manahov et al., 2014).

Against general assumptions claiming that dark pools are detrimental to market efficiency, Zhu (2014) introduces a theory suggesting that dark pools could be beneficial for price discovery, at least in normal market conditions. Comerton-Forde and Putniņš (2015) provide empirical evidence supporting some of those views. The beneficial effects result from dark pools attracting uninformed traders while concentrating informed traders into the exchange which consequently enhances price discovery in the exchange (Comerton-Forde & Putniņš, 2015; Zhu, 2014). The order execution risk between the dark pool and the exchange is the major factor in why informed traders drift into the exchange (Zhu, 2014). In exchanges, all orders are executed at bid or ask price whereas dark pools execute orders at the midpoint of the bid and ask but cannot ensure execution since there are no market makers to secure liquidity in dark pools. Zhu (2014) refers to the heavier side of the market which contains more orders that are enabled to execute because there are not enough counterparties on the other side of the trade. Informed orders are generally positively correlated with stock value so they shift to the heavier side of the market and are more likely left unexecuted in the dark pool (Zhu, 2014). Uninformed orders, on the contrary, are not correlated with each other which is why they have a high execution rate in dark pools. As a result, the noise in exchange is reduced and price discovery improves as informed traders rather trade in exchanges where their orders are more likely executed (Zhu, 2014).

The model has also some drawbacks considering the effects of dark pools. Zhu (2014) notes that dark pools may mitigate welfare impacts as they decrease liquidity in exchanges. More informed traders in exchanges increase adverse selection which results in wider spreads and stronger price effects indicating lower liquidity. As illustrated earlier, informed traders need noise traders to provide necessary liquidity and to shield their trades so that prices would not reveal too much of their private information (Zhu, 2014). This maintains information acquisition profitable enough for informed traders.

Comerton-Forde and Putniņš (2015) suggest that the overall implications of dark pools depend on the quantity of dark trading. A moderate level of dark trading is not disadvantageous and could even benefit typical stocks whereas high levels of dark trading can potentially be detrimental to price discovery. Zhu (2014) consistently suggests that extreme levels of dark trading lead to higher adverse selection and growth in spreads. Thus, excessive dark trading discourages informed traders from acquiring expensive new information which prevents incorporation of fundamental information into prices. Yet, Comerton-Forde and Putniņš (2015) expect dark pools to become more remarkable in price discovery along with growing dark trading volume, although their share in price discovery develops at a slower rate than their market share. The authors find disadvantages both in large and small stocks during the whole sample period of high-level dark trading. However, dark trading stays at decent levels for most stocks in normal market conditions (Comerton-Forde & Putniņš, 2015).

5 Data and empirical methodology

The empirical approach of this thesis is based on the methodology used by Gider et al. (2019) who compare stock price informativeness before and after HFT presence in a market using staggered DiD design. The authors utilize previous research of Aitken et al. (2015) that provides the estimated start dates of HFT in each market obtained by using generally known proxies of HFT activity such as high cancel-to-trade ratio, small average trade size, and co-location. Due to the massive quantity of intraday trading data, this thesis also utilizes already existing empirical literature in estimating HFT entrance. This allows directing full attention to the main issue of price informativeness. First, the main analysis regresses future cash flows to current market prices and examines how this price informativeness measure evolves after HFTs enter the market. Then, the robustness of the results is ensured by using an additional informativeness measure of price synchronicity. Finally, this chapter introduces the panel data of this thesis.

5.1 Price informativeness about future cash flows

First, this thesis examines the relationship between HFT presence and stock price informativeness about future cash flows following the methodology of Gider et al. (2019). The authors use the price informativeness measure regarding future cash flows introduced by Bai et al. (2016) which measures the variation between estimated future cash flows and current market prices. This measure illustrates how much stock prices contain information about a company's future cash flows. Bai et al. (2016) describe it as a welfare-based measure of price informativeness that reveals unviable companies from the ones that will be profitable in the future. Stock price informativeness is consistently measured by comparing future earnings to current stock returns in many other studies (see Collins et al., 1994; Durnev et al., 2003; Gelb & Zarowin, 2002; Lundholm & Myers, 2002). Thus, the stock price informativeness is estimated for each stock and every year for all five forecasting horizons using the cross-sectional forecasting regression equation introduced by Bai et al. (2016):

$$\frac{E_{i,t+h}}{A_{i,t}} = a_{m,t,h} + b_{m,t,h} \log\left(\frac{M_{i,t}}{A_{i,t}}\right) + c_{m,t,h}\left(\frac{E_{i,t}}{A_{i,t}}\right) + d_{m,t,h}\, SIC_{i,t} + \varepsilon_{i,t,h} \qquad (9)$$

Here, future cash flows from one to five-year horizon (h) regressed on current stock market values for each market (m) at the end of each fiscal year (t). E stands for EBITDA (earnings before interest, taxes, depreciation, and amortization), i for each company, M for market capitalization, SIC for a company's sector (first digit of the SIC code) and ε for an error term. Current earnings and industry are controlled to exclude crediting markets which contain obvious public information (Bai et al., 2016). All variables are scaled by the company's total assets (A). Bai et al. (2016) use EBIT (earnings before interest and taxes) as a cash flow variable due to its extensive availability in their data set. However, the authors note that this price informativeness measure is robust also when using other earnings variables such as EBITDA. Thus, this thesis rather uses EBITDA as a cash flow variable because it is not affected by differing accounting practices or capital structures (Durnev et al., 2003). The log ratio of market capitalization to total assets is taken to decrease skewness in the data (Bai et al., 2016).

Price informativeness here is the expected variance of future cash flows from market prices. Bai et al. (2016) take a square root from the price informativeness measure to convert results into relevant units, meaning forecasted future cash flows per one euro of total assets. Consequently, stock price informativeness $(priceinfo)$ in a market (m), year (t) and horizon (h) equals the cross-sectional standard deviation (σ_t) of the $\log(M/A)$ variable multiplied by the forecasting coefficient (b) estimated in Equation 9:

$$\left(\sqrt{priceinfo}\right)_{m,t,h} = b_{m,t,h} \times \sigma_t \left(\log\left(\frac{M}{A}\right)\right) \qquad (10)$$

Then proceeding as in Gider et al. (2019), a staggered DiD test is used to compare price informativeness in different states before and after HFT presence. DiD method is successfully applied in prior HFT research for instance by Lee and Watts (2021) who use its traditional form including a control group, and Malceniece et al. (2019) who utilize the staggered HFT entrance across markets. HFT dummies are regressed on the price informativeness measure obtained above (see Equation 10) according to the estimation function introduced by Gider et al. (2019):

$$priceinfo_{m,t,h} = \beta_0 + \beta_1 \, HFT_{m,t} + \delta \, controls_{m,t} + \eta_t + \mu_i + \varepsilon_{m,t} \qquad (11)$$

In the equation, the price informativeness about future cash flows $(priceinfo)$ in horizon (h) is regressed with the HFT dummy variable (HFT) which is zero prior to HFT presence and one after. Control variables $(controls)$ including firm age and a natural logarithm of market size, firm size, and stock price are added to exclude any changes in these variables that could bias the price informativeness effect. Firm size is a company's market capitalization and the combined market capitalization of all companies in each market equals market size. Market size is controlled because large markets involve more market participants and are therefore generally perceived as more efficient than small markets. Furthermore, old stocks tend to have more accurate prices since investors become more familiar with the time-invariant company characteristics as a company grows older (Dasgupta et al., 2010). Firm size is controlled because big firms are shown to involve less valuation errors as they tend to be more stable and have lower trading costs than small firms (Bessembinder & Kaufman, 1997; Loughran & Ritter, 2000; Fama & French, 1993). Finally, the share price is controlled as it is negatively correlated with liquidity and thus price informativeness (Chordia et al., 2008).

Gider et al. (2019) also include a dummy variable indicating a transition to an electronic trading system in a venue. However, controlling electronic trading is unnecessary in this sample since all of the four Nordic markets have adopted electronic trading systems already by 1989 (Jain, 2005) – a decade before the start of the observation period in this thesis. Staggered HFT entry between the markets provides sufficient setting for DiD analysis allowing two-way fixed effects: firm (μ_i) and year (η_t) level which outline confounding common trends and any time-independent company features that are not driven by HFT entrance (Gider et al., 2019; Malceniece et al., 2019). Finally, clustering standard errors at the firm level controls correlated errors that may result from heterogeneous company characteristics (Weller, 2018). Firm-level clustering also provides the most clusters in this sample and more clusters stabilize standard errors more efficiently leading to more reliable results (Bhattacharya et al., 2020).

5.2 Price non-synchronicity

To test the robustness of the results, the second hypothesis utilizes price non-synchronicity as an alternative measure of price informativeness similarly as in Gider et al. (2019), Lee and Watts (2021), and Weller (2018). Price non-synchronicity is a residual of stock returns that cannot be explained by asset pricing factors. Originally Roll (1988) suggests that this remaining residual could result from noise or private information and proposes the following regression equation derived from asset pricing models:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}\, r_{m,t} + \gamma_{i,t}\, r_{SIC,t} + \varepsilon_{i,t} \tag{12}$$

Here, the yearly returns ($r_{i,t}$) of a company (i) are regressed on market return ($r_{m,t}$) and industry return ($r_{SIC,t}$). Residual ($\varepsilon_{i,t}$) is the firm-specific return unexplained by the market and industry returns. Market and industry returns are value-weighted averages of all stocks in a given market or industry, excluding the stock i in question (Durnev et al., 2003):

$$r_{m,t} = \frac{\sum w_{i,t}\, r_{i,t} - w_{i,t} r_{i,t}}{X_m - 1} \tag{13}$$

Here, w is the value weight that is obtained by scaling the company's market capitalization with the market's total market capitalization. The number of stocks in a particular market is denoted as X_m. Stock i is excluded to avoid false correlations in case the stock is dominant in a certain industry or market. Industry returns are calculated in the same manner.

Based on the Roll's (1988) R^2 measure, Durnev et al. (2003) further derive the following price non-synchronicity measure:

$$1 - R^2 = \frac{\varepsilon_{i,t}^2}{\left(r_{i,t} - \mu_{i,t}\right)^2} \tag{14}$$

In the equation, Roll's (1988) R^2 describes return variance explained by the market and industry factors. $1 - R^2$, on the contrary, is an inverse measure of R-squared indicating the firm-specific return variance which is the variance of the unexplained residual $\left(\varepsilon_{i,t}^2\right)$ scaled by the total variance of the stock $\left(r_{i,t} - \mu_{i,t}\right)^2$. Durnev et al. (2003) scale the residual variance with the total variance of a stock because some businesses are more sensitive to systematic shocks and industry factors and may therefore experience amplified reactions to firm-specific events. These sensitive businesses potentially over-adjust to the firm-specific news due to environmental uncertainty. Moreover, Durnev et al. (2003) find a positive correlation between price non-synchronicity and price informativeness about future cash flows indicating that price non-synchronicity is a sufficient measure of price informativeness.

Finally, the non-synchronicity measure obtained from Equation 14 is regressed on the HFT dummy variable similarly as in the main price informativeness estimation about future cash flows. Most of the firm characteristics and market variables are controlled consistently with Gider et al. (2019) including inflation, GDP growth rate, and natural logarithm of stock price, firm size, and GDP. Year and firm effects are fixed and standard errors are clustered at the firm level likewise with the main analysis to achieve comparable results. Thus, the development of price non-synchronicity ($nonsynch$) around HFT entrance is estimated as follows:

$$nonsynch_{m,t,h} = \beta_0 + \beta_1 \, HFT_{m,t} + \delta \, controls_{m,t} + \eta_t + \mu_i + \varepsilon_{m,t} \tag{15}$$

5.3 Data sample

The annual data sample period spans from the end of the year 1999 to the end of 2013 and covers publicly listed companies of four Nordic exchanges: Helsinki, Stockholm, Oslo and Copenhagen. The end-of-year share prices, market indices and firm-level accounting data are collected from Thomson Reuters Refinitiv. Consumer Price Index (CPI) data is also from Thomson Reuters Refinitiv and it is used to exclude the inflation effect since only real values matter in assessing HFTs' influence on price informativeness. All the variables are converted into real values using 1999 as a base year. Industry division definitions for each SIC code are obtained from the United States Department of Labor (2023). Furthermore, the different currencies of the Nordic markets are converted into comparable euro values by using exchange rates from the European Central Bank (2022). The gross domestic product (GDP) from The World Bank (2023) is also inflation and currency-adjusted for each country.

Table 1 presents the descriptive statistics of 242 listed common stocks that provide price, total assets, market capitalization, EBITDA, and SIC-code observations for each year throughout the 14-year period. HFT entrance years are excluded from the sample. Duplicate class A stocks, preferred stocks and companies that are delisted or merged during the sample period are omitted as done in Durnev et al. (2003) and Lee and Watts (2021). The banking and financial sector (SIC 6000-6999) is excluded due to the distinctive nature of the business, and accounting data that is incomparable with other industries (Bai et al., 2016; Gider et al., 2019; Durnev et al., 2003). Furthermore, all continuous variables are winsorized at the bottom 1% and top 99% levels which means that any outside observations are replaced by the value at the specified percentiles. This is generally used method in HFT and price informativeness research to limit the effect of outliers and exclude potentially impossible values (see e.g., Bai et al., 2016; Chen et al., 2007; Lee & Watts, 2021; Malceniece et al., 2019; Weller, 2018). The minimum values of the price informativeness measure are negative for each horizon which illustrates that there are times when stocks are negatively priced in relation to future cash flows.

Table 1. Descriptive statistics of the data sample from 1999–2013.

Variable	Obs	Median	Mean	SD	Min	Max
HFT (d)	3388	0	0.459	0.498	0	1
Priceinfo (h=1)	3388	0.086	0.080	0.073	-0.379	0.322
Priceinfo (h=2)	3388	0.085	0.080	0.058	-0.342	0.283
Priceinfo (h=3)	3388	0.086	0.082	0.051	-0.288	0.264
Priceinfo (h=4)	3388	0.087	0.084	0.047	-0.232	0.275
Priceinfo (h=5)	3388	0.087	0.084	0.044	-0.181	0.270
Nonsynch	3146	0.196	0.472	0.722	0.000	8.071
Market cap (mil. €)	3388	0.120	1.027	2.996	0.002	21.800
Total assets (mil. €)	3388	0.169	1.130	2.785	0.003	18.400
Log market cap	3388	11.693	11.846	2.028	7.744	16.899
Log (market cap/assets)	3388	-0.364	-0.357	0.867	-2.559	1.972
EBITDA/assets	3388	0.113	0.100	0.135	-0.553	0.423
Firm age	3388	13	14.123	7.533	1	36
Log price	3388	1.602	1.651	1.732	-1.976	8.986
Log market size	56	18.029	18.013	0.682	16.617	19.397
Log GDP	56	26.355	26.367	0.273	25.842	26.849
GDP growth rate (%)	52	2.001	1.516	6.500	-19.834	19.191
Inflation rate (%)	52	1.898	1.783	0.972	-0.317	3.681

HFT entry dates in Table 2 are collected from the previous research of Aitken et al. (2015) and Klein and Song (2021). Aitken et al. (2015) provide estimated HFT start dates of multiple international markets according to general HFT proxies such as average trade size, order cancellation and co-location. The decrease in trade size provides HFT start dates for both Sweden and Norway. Gider et al. (2019) find no significant relation between co-location dates and price informativeness which is why we rather use start dates based on trade size. Moreover, Aitken et al. (2017) show that HFTs were already effective years before co-location officially started so it should be considered more as a consequence of HFT. Gider et al. (2019) create a dummy variable of HFT presence by using order cancellation rate as a primary HFT indicator and trade size as an alternative indicator for markets that lack order cancellation statistics.

Table 2. Proxies of HFT entry dates (Aitken et al., 2015; Klein & Song, 2021).

Stock exchange	Country	Trade size	Cancellation	Co-location	Chi-X
Nasdaq Copenhagen	Denmark				06/2008
Nasdaq Helsinki	Finland				04/2008
Nasdaq Stockholm	Sweden	04/2005		03/2011	03/2008
Oslo Stock Exchange	Norway	04/2005	02/2005	04/2010	06/2008

Since there is no previous research providing HFT start dates in Finland or Denmark, alternative indicators of HFT activity are also required in this thesis. Klein and Song (2021) present the start dates of the Chi-X multilateral trading facility in European markets including all of the four Nordic markets subject of this study. Chi-X is an alternative trading venue which tends to attract HFTs because of its latency improvements and it has been shown to significantly increase HFT activity since its introduction (Klein & Song, 2021; Malceniece et al., 2019; Menkveld, 2013). Hence, it can be considered as a suitable indicator of HFT activity as Menkveld (2013) and Malceniece et al. (2019) do in their studies. Following the example of Gider et al. (2019), the HFT dummy variable is determined by using two different HFT indicators depending on the data availability in the given market: according to trade size in Norway and Sweden, and Chi-X in Denmark and Finland.

These two different HFT indicators provide a staggered setting of HFT entry. According to trade size, HFTs entered the Oslo and Stockholm markets in 2005 whereas in Copenhagen and Helsinki, the Chi-X trading facility began its operation in 2008. Consequently, Denmark and Finland serve as a control group for Sweden and Norway treated in 2005 when HFT activity had not yet started in Denmark and Finland. Already-treated Sweden and Norway, on the other hand, serve as a control group for Denmark and Finland treated in 2008. In other words, the later-treated markets work as a control group for markets being treated at the time and vice versa. Therefore, staggered HFT entry spares from including a separate control market without any HFT activity.

6 Results

This chapter begins by first presenting the results of the main analysis between HFT presence and stock price informativeness. This is followed by a robustness check which is carried out by regressing the HFT dummy with the stock price non-synchronicity measure. After that, the chapter continues to cross-sectional tests to see how HFT presence affects small versus large and young versus old companies. Finally, the potential influence of economic crises is tested by excluding crisis periods and comparing the results to the main analyses.

6.1 HFT and price informativeness

Table 3 presents the results of the main analysis in which the HFT dummy is regressed on stock price informativeness about future cash flows. Results indicate a moderate positive correlation between HFT entrance and price informativeness. The positive coefficients vary from 0.012 in the one-year horizon to 0.005 in the five-year horizon. The results are statistically significant at the 1% level for the first two horizons and the 5% level for the rest of the forecasting horizons. The positive effect is economically most significant in the two-year horizon where one standard deviation increase in HFT leads to an 8.6% increase in price informativeness whereas the least significant effect is observed in the five-year horizon where the relative increase is 5.7%. On average of all horizons, price informativeness increases 6.9% per one standard deviation increase in HFT and 9.1% in relation to the median value of the price informativeness measure. The adjusted R-squared shows that the estimation is successful in explaining around 58–64% of the price informativeness variation depending on the forecasting horizon.

Table 3. Stock price informativeness about future cash flows.

This table presents the coefficients of the HFT dummy regressed on the price informativeness measure for each one to five-year horizon (h). Log market size, log firm size, firm age and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. T-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Priceinfo	h = 1	h = 2	h = 3	h = 4	h = 5
HFT (d)	0.012***	0.010***	0.006**	0.006**	0.005**
	(2.84)	(2.98)	(2.11)	(2.34)	(1.97)
Log market size	0.013***	0.008***	0.006***	0.006***	0.006**
	(3.00)	(2.87)	(2.67)	(2.66)	(2.60)
Log firm size	0.040***	0.027***	0.022***	0.020***	0.018***
	(6.68)	(5.09)	(4.62)	(4.79)	(4.98)
Firm age	-0.001	-0.001	-0.002	-0.001	-0.001
	(-0.12)	(-0.46)	(-0.66)	(-0.54)	(-0.46)
Log price	-0.014**	-0.012**	-0.011**	-0.010**	-0.009**
	(-2.19)	(-2.11)	(-2.18)	(-2.27)	(-2.45)
Constant	-0.607***	-0.350***	-0.250***	-0.232***	-0.203***
	(-5.29)	(-4.45)	(-3.64)	(-3.53)	(-3.28)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	3388	3388	3388	3388	3388
R^2	0.609	0.662	0.671	0.664	0.671
Adjusted R^2	0.576	0.633	0.643	0.636	0.643
Clustered by	Firm	Firm	Firm	Firm	Firm

The results in Table 3 provide evidence supporting the rejection of the null hypothesis according to which there would be no relation between HFT presence and stock price informativeness about future cash flows. However, the positive sign of the obtained coefficients indicates the opposite of the presumption of the first hypothesis:

H_1: HFT reduces stock price informativeness about future cash flows.

Thus, the first hypothesis of this thesis is rejected. The results on the contrary imply that stock prices become a bit more accurate estimates of future cash flows after HFTs enter the Nordic markets. This positive correlation between HFT entrance and price informativeness contradicts most of the similar HFT publications regarding long-term price informativeness. Gider et al. (2019), whose research setting this paper largely follows, discover significant negative relation between HFT and price informativeness about future cash flows through two to five-year horizons. The coefficient in their one-year horizon is also negative but insignificant. Contrary to the results in Table 3, their international data sample suggests that HFT presence has a detrimental impact on price informativeness. Furthermore, the authors conclude that price informativeness weakens especially for longer horizons as the magnitude of the negative coefficients increases along with the growing horizon. Results in Table 3 instead indicate that the HFT effect on price informativeness is strongest for the first two horizons after which the magnitude of the positive coefficients declines to quite moderate levels. This seems logical as it is more challenging to estimate future cash flows for longer forecasting horizons.

Besides the working paper by Gider et al. (2019), there are currently no other studies that examine HFTs' implications on price informativeness at the annual level. However, prior studies by Weller (2018) and Lee and Watts (2021) discover that the trades of HFTs are negatively associated with stock price informativeness around earnings news. The reductions in information acquisition are observed one to three months before the announcement. These studies unanimously suggest that HFT presence reduces the incentives for fundamental information acquisition causing less informative prices. One potential explanation is that some aggressive HFTs screen the order flow and exploit the obtained information in forecasting the future order flow for their own gain which raises the transaction costs for other informed traders (Baldauf & Mollner, 2020; Gider et al., 2019; Yang & Zhu, 2020). Achieving a profitable informational edge becomes more challenging also because liquidity providing HFTs decrease information asymmetry by reducing adverse selection and spreads (Baldauf & Mollner, 2020).

Contrary to the papers above, Bhattacharya et al. (2020) along with Chordia and Miao (2020) suggest that HFTs further the incorporation of fundamental information into stock prices. Bhattacharya et al. (2020) find that HFT-traded stocks adapt to earnings announcements faster as shown by the 46% higher earnings response coefficient (ERC) on the announcement day. The result is driven by liquidity supplying HFTs and is observed three hours post-announcement until the end of the trading day. Consistently, Chordia and Miao (2020) record nearly two times larger abnormal return difference between the highest and the lowest SUE deciles in HFT-traded stocks two days post-announcement. They also detect significantly lower PEADs three months after an announcement stating that the positive contribution on price efficiency could last up to a year post-announcement. In addition, Bhattacharya et al. (2020) observe a reduced price impact of trades which indicates a decline in information asymmetry between informed and uninformed traders after the announcement. These papers argue that larger price reactions together with reduced price drift and information asymmetry indicate enhanced price discovery and thus price informativeness around earnings news. Results in Table 3 are compatible with these statements, although Bhattacharya et al. (2020) perceive these results at a remarkably shorter intraday post-announcement period. It is also unclear how reduced post-announcement price drift could enhance price informativeness for up to a yearlong period as pointed out by Erhard and Sloan (2020). Moreover, these methodologies capture the incorporation of already existing information but do not address the possibility that the increased ERCs and SUEs could be explained by the reduced information acquisition before the announcement.

The results presented in Table 3 contradict most of the prior studies and thus challenge the view that HFT would unambiguously diminish stock price informativeness. Instead, these results indicate that long-term stock price informativeness regarding projected cash flows slightly increases after HFTs enter the Nordic markets. The contradiction between the incorporation of existing information and acquiring new information persists, but these results propose that the potential decline in information acquisition is not significant enough to undermine stock price informativeness in the long term. So, even though the acquisition of private unpublished information may have become less awarding and thus scarce, Bhattacharya et al. (2020) suggest that the informational gap is filled more sufficiently after the information is published. Consequently, the fundamental information will be incorporated into stock prices eventually, and prices will remain true to their intrinsic values in the long term. Chordia and Miao (2020) also remark that HFT algorithms are not burdened by humane psychological and behavioural characteristics that occasionally cause irrationalities in the markets. Limited investor attention, momentum and disposition effect are only a few examples of commonly recognized behavioural anomalies which are shown to disrupt efficient asset pricing (see e.g., Frazzini, 2006; Hirshleifer et al., 2009; Jegadeesh & Titman, 1993; 2001).

The deviant outcomes in Tabel 3 should be critically evaluated due to the shared timing of the HFT entrance in Norway and Sweden in 2005, and in Denmark and Finland in 2008. This raises concerns about whether the treatment effect is staggered enough between these groups. The growing popularity of staggered DiD methodologies among natural experiments is based on the rollout exogeneity assumption, according to which a random staggered treatment through time is less likely to be interfered by other confounding trends that could bias the observed outcome effect (Baker et al., 2022). However, closely staggered HFT entrance between these markets increases the risk of common confounding trends which could potentially erode the robustness of these estimations.

Moreover, recent developments in staggered DiD research have shown that two-way fixed effects could potentially lead to biased estimations when used with time-varying treatment effects (see Baker et al., 2022; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021). The level of HFT activity is unlikely to remain constant over time between markets and traded stocks after the treatment. This dynamic nature of HFT presence induces to the bad comparisons problem in which the coefficients of already-treated markets are contaminated by the changes in HFT activity, making them insufficient reference points for later-treated markets (Baker et al., 2022; Goodman-Bacon, 2021). Thus, the time-variant HFT treatment effect combined with two-way fixed effects in staggered DiD design might lead to potentially biased significant results regarding the size or even sign of the effect. So even though the HFT treatment years – which presumably associate most variation in HFT activity – are omitted from the sample, these results should be construed with caution. Especially, when it comes to such long-term estimations without never-treated control groups (Baker et al., 2022; Goodman-Bacon, 2021).

6.2 HFT and price non-synchronicity

Table 4 presents the results of regressing HFT on stock price non-synchronicity. The estimation provides a -0.161 coefficient between HFT introduction and stock price non-synchronicity when control variables and fixed effects are excluded. This equals an 11.1% reduction in non-synchronicity per one standard deviation of HFT presence and an 82.1% decline per median value of the non-synchronicity measure. The result is statistically significant at the 1% level. However, when control variables and both fixed effects are taken into account, the coefficient drops to only -0.017. This means that one standard deviation increase in HFT would result in a 1.2% decline in non-synchronicity and an 8.7% reduction per median value. The result also becomes statistically insignificant. Such a remarkable difference shows that the non-synchronicity coefficient without control variables or fixed effects is potentially biased by other confounding factors. Furthermore, the estimations are sufficient in explaining only 1.2–3.6% of the non-synchronicity variation as shown by the adjusted R-squared.

Thus, the results in Table 4 provide insufficient evidence to support the rejection of the null hypothesis. Since the estimation including control variables and fixed effects offers insignificant results, the null hypothesis that there is no relation between HFT presence and price non-synchronicity must be accepted. Consequently, the second hypothesis of this thesis is rejected:

H_2: HFT decreases stock price non-synchronicity.

Table 4. Stock price non-synchronicity.

This table presents the coefficients of the HFT dummy regressed on price non-synchronicity measure. Log price, log firm size, log GDP, GDP growth and inflation serve as control variables in the second and third estimations. Year and firm fixed effects are included according to the table and standard errors are clustered at the firm level. T-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

	(1) Nonsynch	(2) Nonsynch	(3) Nonsynch
HFT (d)	-0.161***	-0.038	-0.017
	(-6.23)	(-0.57)	(-0.26)
Log price		-0.011	0.012
		(-1.26)	(0.52)
Log firm size		-0.023***	-0.065*
		(-3.26)	(-1.96)
Log GDP		-0.189***	-0.006
		(-3.51)	(-0.02)
GDP growth		-0.001	-0.001
		(-0.21)	(-0.31)
Inflation		0.051***	0.058***
		(2.87)	(2.91)
Constant	0.552***	5.672***	1.287
	(29.30)	(3.98)	(0.13)
Year FE	No	Yes	Yes
Firm FE	No	No	Yes
Observations	3146	3146	3146
R^2	0.012	0.042	0.112
Adjusted R^2	0.012	0.036	0.031
Clustered by	Firm	Firm	Firm

The rejection of the second hypothesis prevents from ensuring the robustness of the first hypothesis stating that HFT presence improves price informativeness about future cash flows. Price synchronicity is a generally used alternative measure for price informativeness. Bhattacharya et al. (2020), Gider et al. (2019), Lee and Watts (2021), Malceniece et al. (2019) and Weller (2018) utilize it to ensure the robustness of their price informativeness estimations and they all find that HFT presence increases the stock price synchronicity. However, there are some conflicting interpretations between these studies similarly as the research field divides on whether price synchronicity equals less or more informative prices. Bhattacharya et al. (2020) examine price synchronicity from the angle of industry-wide news. Their findings show that HFT-traded stock returns become more synchronised after simultaneous earnings announcements in a shared industry. According to their interpretation, this means that industry-level information is incorporated into prices more efficiently after the announcement. Malceniece et al. (2019) consistently show that approximately 30% of the increased return synchronicity post-HFT entrance is explained by the more efficient incorporation of market-level information and 60% by HFTs correlating statistical arbitrage strategies. In other words, these studies suggest that prices are more synchronized because they contain more industry and index-level information.

Lee and Watts (2021) and Weller (2018) consistently find significant reductions in the price non-synchronicity of HFT-traded stocks pre-announcement period. Similarly, Gider et al. (2019) discover a 15% reduction in price non-synchronicity per standard deviation after HFTs enter the market. Yet, these studies state that reduced non-synchronicity indicates less informed stock prices about firm-specific fundamentals. Weller (2018) controls the confounding effects of industry and market factors and correlating HFT strategies by comparing non-synchronicity in normal versus event times. Pre-event periods generally include more acquirable firm-specific information so greater difference demonstrates improved responsiveness to firm-specific news while excluding the influence of statistical arbitrage. Weller (2018) finds that HFT presence leads to a significant reduction in non-synchronicity before news announcements indicating reduced price informativeness regarding firm-specific information.

Furthermore, the potential changes in the share of institutional ownership or exchange-traded funds (ETFs) are not controlled during the observation period. Hence, the possible contribution of these factors cannot be completely ruled out. The level of institutional holdings may have a positive or negative impact on return synchronicity depending on the length of an institution's investment horizon. Dedicated institutional investors with long investment horizons and large holdings are committed to monitoring and acquiring costly firm-specific information reducing price synchronicity whereas transient investors with large portfolio turnovers increase price synchronicity as their trading pursues quick profits (An & Zhang, 2013; Barka et al., 2023). Inadequate company reporting and investor monitoring centralize risk and firm-specific information to the corporate management causing more synchronized and therefore less informative stock prices (Jin & Myers, 2006). Gider et al. (2019) find that institutional investors reduce approximately 40% of their holdings and 60% of their trades per one standard deviation after HFTs enter the market. This means that they rather replicate market indices instead of acquiring firm-specific information which again leads to less informative prices. Israeli et al. (2017) show that ETF holdings increase price synchronicity by attracting uninformed traders away from the individual security market. This also reduces market liquidity because the available number of outstanding individual stocks decreases as shares become part of an indexed ETF. Consequently, liquidity declines and trading costs rise in the stock market undermining the profitability of firm-specific information acquisition.

The results in Table 4 provide insufficient evidence to demonstrate the relation between HFT presence and price non-synchronicity. Instead, these results lead to the conclusion that there is no significant change in price non-synchronicity after HFTs enter the Nordic markets. However, confounding factors like ETFs and institutional holdings may contribute to these deviating results. Moreover, these estimations do not specify whether the impact stems from enhanced inclusion of market information or deterred acquisition of firm-specific information so the effects might cancel each other out.

6.3 Firm size and age

This section presents the results of the cross-sectional tests between small and big companies as well as young and old companies to see whether HFT presence has differing impacts depending on firm age or size. Companies are divided into small or big and young or old companies according to whether they are above or below the median firm size or age within each market and year, following the procedure in Gider et al. (2019). The small firm dummy is one if a company’s market capitalization is below the median value within a given market and year, and zero otherwise. The large firm dummy is generated vice versa.

Table 5 reports the results of two cross-sectional estimations between HFT and small firms versus HFT and big firms. The coefficient difference reveals whether the effect of HFT presence differs between small and big companies. Control variables are retained otherwise consistent with the main estimation except the firm size control is excluded as it is the core interest of this estimation. Including an interaction term in the regression changes the interpretation of the interacting variables, and thus the results of these two cross-sectional estimations are reported in a combined table for more explicit presentation. Small and big firm dummy coefficients report the effect when the interaction variable is zero. For example, the big firm dummy shows that large firm stocks are 0.023 coefficients more informative on average than small stocks when HFTs are not present.

Table 5. Cross-sectional tests between small and big companies.

This table presents the coefficients of cross-sectional tests between small and big firms where the HFT dummy is regressed on price informativeness measure for each one to five-year horizon (h). Log market size, firm age and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. Z-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Priceinfo	h = 1	h = 2	h = 3	h = 4	h = 5
Small firm (d)	-0.035***	-0.024***	-0.019***	-0.019***	-0.017***
	(-4.62)	(-4.11)	(-3.88)	(-4.09)	(-4.16)
Big firm (d)	0.035***	0.024***	0.019***	0.019***	0.017***
	(4.62)	(4.11)	(3.88)	(4.09)	(4.16)
HFT x small firm	0.021***	0.016***	0.012***	0.011***	0.010***
	(3.50)	(3.62)	(3.03)	(3.21)	(2.96)
HFT x big firm	0.004	0.003	0.000	0.001	0.000
	(0.81)	(0.93)	(0.12)	(0.38)	(0.09)
Coeff. difference	0.017***	0.013***	0.011***	0.010***	0.009***
	(2.98)	(3.12)	(3.15)	(3.15)	(3.13)
Log market size	0.017***	0.010***	0.008***	0.008***	0.007***
	(3.63)	(3.53)	(3.25)	(3.21)	(3.10)
Firm age	0.001	-0.001	-0.001	-0.001	-0.001
	(0.12)	(-0.28)	(-0.55)	(-0.46)	(-0.40)
Log price	0.006	0.002	0.000	0.000	-0.000
	(1.36)	(0.46)	(0.05)	(0.05)	(-0.08)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3388	3388	3388	3388	3388
Clustered by	Firm	Firm	Firm	Firm	Firm

Results in Table 5 show that the HFT effect is economically and statistically more significant on small firms. HFT improves the price informativeness of small firms by 0.021–0.010 coefficients and the effect weakens along with the growing horizon. The positive effect is significant at 1% for all five forecasting horizons. Meanwhile, large firms are unaffected by the HFT presence as shown by the statistically insignificant coefficients which vary between 0.004 and zero. The coefficient difference represents the actual interaction term between HFT and small firms (or large firms), confirming that the difference between small and big firms is statistically significant at the 1% level in all horizons. On average, HFT increases the price informativeness of small firms by 0.012 coefficients more than of big firms. The figures in Appendix 2. graphically demonstrate this distinction as shown by the steeper curves of the predictive margins of small stocks compared to large stocks.

These results harshly contradict the prior studies stating that HFTs tend to trade large liquid stocks over small stocks (Brogaard et al., 2014; Chordia & Miao, 2020). Hendershott et al. (2011) consistently show that HFT increases liquidity and reduces spreads, especially for large stocks leading to more informative quotes. Gider et al. (2019) also find that large stocks are more strongly affected by the HFT presence than small stocks, but the effect on price informativeness is negative. Results in Table 5 inconsistently indicate a stronger HFT effect on small stocks which raises concerns whether the observed positive effect on price informativeness truly results from HFT activity. As illustrated earlier, ETF and institutional holdings may have conflicting, but significant influence on price synchronicity. Thus, the impact of these factors should be more closely addressed as potential explanations behind the deviating price informativeness results.

First, growing ETF activity shares a similar contradiction between price discovery of already existing information and acquisition of new fundamental information as HFT presence. Prior studies generally agree that ETF holdings improve short-term price discovery, but the long-term perspective is yet unexplored (Glosten et al., 2021; Ivanov et al., 2013). Israeli et al. (2017) provide novel evidence showing that ETF's positive effect on price informativeness turns negative over quarter-long horizons. The authors reason their findings by deterring information acquisition that is due to increased trading costs caused by ETFs. Gider et al. (2019) observe a supporting negative relation between ETF trading volume and price informativeness. According to these studies, growth in ETF market share should diminish long-term price informativeness, so it is unlikely to explain the positive price informativeness effect.

Secondly, the influence of institutional investors should be considered since they are one of the most powerful shareholders. Institutional investors are generally perceived as more informed than retail investors due to their superior experience and resources in acquiring, analysing, and interpreting fundamental information (An & Zhang, 2013). Hence, more frequent trades and greater holdings of institutional investors are shown to increase the information content of stock prices (see e.g., Boehmer & Kelley, 2009; Gallagher et al., 2013; Luo et al., 2014). As mentioned earlier, institutional investors may have a positive or negative impact on price synchronicity depending on whether they are dedicated or transient investors (An & Zhang, 2013; Barka et al., 2023). These studies suggest that an increase in institutional investor ownership, especially of dedicated investors, could positively contribute to price informativeness during HFT entrance. Yet, the more pronounced effect on small stocks does not imply that institutional investors would drive the growth in price informativeness since they prefer to hold and trade large liquid stocks with low transaction costs (Boehmer & Kelley, 2009; Gallagher et al., 2013).

The results in Table 5 confirm that HFTs' positive impact on price informativeness cannot be explained by reverse causality which is a common concern in similar HFT papers. For example, Gider et al. (2019) and Weller (2018) address the HFTs' potential preference to trade insufficiently priced stocks which could bias the negative relation between HFT and price informativeness indicated by their results. Similarly, Chordia and Miao (2020) consider the possibility of reverse causality distorting their findings of a positive correlation between HFT and price efficiency. In their case, the effect could be falsely attributed by the HFTs' tendency to trade large and liquid stocks which are already more sufficiently priced. Table 5 proves that the positive price informativeness effect cannot be driven by reverse causality since only less informative illiquid small stocks are significantly affected by the HFT presence. Meanwhile, large stocks are unaffected by the HFT presence.

Erhard and Sloan (2020) propose advanced market microstructure as an alternative explanation that is shown to improve the price efficiency of large liquid stocks whereas small illiquid stocks are unaffected by microstructure development. Haslag and Ringgenberg (2023) show that new exchanges and alternative trading platforms have nearly doubled market fragmentation in the U.S. equity markets during the past two decades. According to the authors, the increased competition lowers trading costs in fragmented markets leading to more frequent and smaller trades of large stocks which consequently become more liquid and efficiently priced. Small stocks on the contrary become less sufficiently priced since they are traded less frequently and in larger trades when fragmentation rises. This is because various trading venues offer more arbitrage opportunities exposing liquidity providers to additional adverse selection risk, particularly with infrequently traded stocks (Baldauf & Mollner, 2021). Thus, liquidity suppliers require wider spreads from small stocks to bear this risk. However, Nordic markets are shown to be prominently less fragmented compared to many other markets (Ntakaris et al., 2018). This could explain the exceptional results in Table 5 as liquidity providing HFTs can settle for smaller spreads in less fragmented Nordic markets. Hence, HFTs could choose to trade small stocks more often contrary to other more fragmented HFT markets where they would face higher adverse selection. Less fragmented markets also provide fewer arbitrage opportunities which could limit HFTs' aggressive liquidity demanding trades and thus explain the insignificant HFT effect on large stocks.

Table 6 presents the results of the cross-sectional tests between HFT and young firms versus HFT and old firms. Here, the young (old) firm dummy is one when a firm's age is below (above) the median age within a given market and year, and zero otherwise. Again, control variables remain the same as in the main estimation, except now the firm age control is excluded. Table 6 shows that HFT has a slightly stronger positive effect on young companies' price informativeness as the coefficient varies between 0.014 and 0.006. The positive effect on young stocks is significant at least 5% level throughout the forecasting horizons. The coefficients of old companies, on the other hand, vary between 0.010 and 0.003 while the effect is statistically significant only for the first two horizons. The magnitudes of the positive HFT dummy coefficients differ by 0.0052 units on average between young and old companies over all horizons. Yet, the difference is statistically insignificant throughout the forecasting horizons.

Table 6. Cross-sectional tests between young and old companies.

This table presents the coefficients of cross-sectional tests between young and old firms where the HFT dummy is regressed on price informativeness measure for each one to five-year horizon (h). Log market size, firm size and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. Z-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Priceinfo	h = 1	h = 2	h = 3	h = 4	h = 5
Young firm (d)	-0.057***	-0.031***	-0.021***	-0.020***	-0.012***
	(-8.49)	(-6.20)	(-4.87)	(-5.13)	(-3.24)
Old firm (d)	0.055***	0.030***	0.020***	0.019***	0.010***
	(8.55)	(6.12)	(4.74)	(4.95)	(2.99)
HFT x young firm	0.014***	0.012***	0.008**	0.008***	0.006**
	(2.92)	(3.27)	(2.51)	(2.63)	(2.24)
HFT x old firm	0.010**	0.007**	0.004	0.004	0.003
	(2.00)	(2.04)	(1.28)	(1.48)	(1.17)
Coeff. difference	0.006	0.006	0.005	0.005	0.004
	(0.99)	(1.20)	(1.19)	(1.25)	(1.27)
Log market size	0.013***	0.008***	0.007***	0.006***	0.006***
	(3.05)	(2.95)	(2.76)	(2.76)	(2.68)
Log firm size	0.040***	0.027***	0.021***	0.020***	0.018***
	(6.70)	(5.10)	(4.61)	(4.79)	(4.97)
Log price	-0.013**	-0.011**	-0.010**	-0.010**	-0.009**
	(-2.14)	(-2.05)	(-2.12)	(-2.21)	(-2.39)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	3388	3388	3388	3388	3388
Clustered by	Firm	Firm	Firm	Firm	Firm

The results in Table 6 indicate that there is no significant difference on how HFT presence affects young versus old companies. Predictive margins in Appendix 3. graphically demonstrate this insignificant difference as shown by the nearly parallel graphs of young and old firms. The result is consistent with the insignificant age control variable in the main analysis (see Table 3). Gider et al. (2019), on the other hand, find that young firms are significantly more affected by the HFT presence than old firms. They argue that the negative price informativeness effect is stronger for young firms because they are more challenging to value and therefore decreased information acquisition affects young companies more severely.

6.4 Economic crises

Chi-X trading platform that serves as an HFT entrance proxy in Denmark and Finland was inconveniently introduced at the same time as the 2008 financial crisis. Therefore, the impact of economic crises should be taken into consideration to ensure that the results are not driven by economic downturns. Gider et al. (2019) test this by performing cross-sectional tests between HFT and crisis dummies and re-running the main test without crisis years. The crisis dummy is generated according to the returns of the main index of each market. If the annual return of a market index is -10% or less, the crisis dummy is one and zero otherwise. The cross-sectional tests of HFT and economic crisis periods fail to provide any results due to multicollinearity between HFT and crisis dummies. However, Table 7 provides insight about controlling crisis periods in the estimation and the results remain nearly unchanged compared to the main regressions in Table 3. Only the statistical significance in the five-year horizon drops from 5% to 10% level and the coefficient in the two-year horizon reduces by 0.001 units.

Table 7. Stock price informativeness controlling economic crises.

This table presents the coefficients of the HFT dummy regressed on price informativeness measure for each one to five-year horizon (h). Crisis dummy, log market size, log firm size, firm age and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. T-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

Priceinfo	(1) h = 1	(2) h = 2	(3) h = 3	(4) h = 4	(5) h = 5
HFT (d)	0.012***	0.009***	0.006**	0.006**	0.005*
	(2.84)	(2.97)	(2.11)	(2.33)	(1.97)
Crisis (d)	-0.006	-0.005	-0.005	-0.004	-0.003
	(-0.72)	(-0.87)	(-0.96)	(-0.77)	(-0.65)
Log market size	0.014***	0.009***	0.007***	0.007***	0.006***
	(3.12)	(3.01)	(2.83)	(2.77)	(2.68)
Log firm size	0.040***	0.027***	0.022***	0.020***	0.018***
	(6.69)	(5.10)	(4.63)	(4.80)	(4.98)
Firm age	-0.001	-0.001	-0.002	-0.001	-0.001
	(-0.12)	(-0.46)	(-0.67)	(-0.55)	(-0.47)
Log price	-0.014**	-0.012**	-0.011**	-0.010**	-0.009**
	(-2.20)	(-2.12)	(-2.18)	(-2.28)	(-2.46)
Constant	-0.619***	-0.360***	-0.260***	-0.240***	-0.209***
	(-5.37)	(-4.47)	(-3.69)	(-3.57)	(-3.34)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	3388	3388	3388	3388	3388
R^2	0.609	0.662	0.671	0.664	0.671
Adjusted R^2	0.576	0.633	0.643	0.636	0.643
Clustered by	Firm	Firm	Firm	Firm	Firm

Detected multicollinearity between HFT and crisis dummies indicates that these independent variables are correlated. This means that economic downturns might falsely contribute to these results. Even though the crisis dummy is insignificant throughout the forecasting horizons in Table 7, highly uncertain periods are generally perceived less sufficient in terms of price informativeness as market panic leads to over-reaction and thus less accurate prices (Lim et al., 2008; Malkiel, 2003). Multiple studies support this by showing that stock return synchronicity increases during economic crises indicating reduced price informativeness about firm-specific fundamentals (see e.g., Elshandidy & Ahmed, 2023; Gupta et al., 2013; Yuan, 2005). Increased trading costs and withdrawal of hedge funds are considered potential reasons behind increased synchronicity during uncertain times (Anand et al., 2013; Ben-David et al., 2012). Furthermore, crisis periods are often associated with increased volatility, but volatility does not always equal diminished price informativeness. Dávila & Parlatore (2023) find opposite relations between volatility and price informativeness depending on the initial informativeness level of a stock: volatility increases the information content of already informative stocks while hampering the informativeness of insufficiently priced stocks.

The HFT effect cannot be directly examined in economic crises due to the collinearity problem and because the exclusion of normal times would eliminate too many observation years for a reliable assessment of HFT implications. To investigate more thoroughly the potential influence of economic crises, the main estimation is repeated with the distinction that crisis periods are now omitted from the sample similarly as in Gider et al. (2019). Table 8 presents the results and shows that the exclusion of crisis years reduces the number of observations from 3388 to 2410 observations. The coefficient of determination of the model slightly improves as demonstrated by the increased R-squared. Keeping everything else constant, Table 8 shows that the economic magnitude of the positive HFT coefficients declines approximately 32% on average for all horizons in comparison to the original estimation in Table 3. This suggests that HFTs' positive contribution to price informativeness is roughly a third less in normal times. On average, price informativeness increases 4.7% per one standard deviation of HFT whilst the relative increase in the main estimation is 6.9% per one standard deviation. This equals a 2.2 percentage point decline in the positive HFT effect per standard deviation of HFT when only economically stable periods are included. Statistical significance drops from the 1% level to 5% level for the first two horizons while in three to four-year horizons, the significance reduces from 5% to only 10% level. HFTs' effect on price informativeness in the five-year horizon falls from the 5% level to statistically insignificant.

Table 8. Stock price informativeness excluding economic crises.

This table presents the coefficients of the HFT dummy regressed on price informativeness measure for each one to five-year horizon (h) while crisis years are excluded. Log market size, log firm size, firm age and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. T-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

Priceinfo	(1) h = 1	(2) h = 2	(3) h = 3	(4) h = 4	(5) h = 5
HFT (d)	0.009**	0.007**	0.004*	0.004*	0.003
	(2.16)	(2.45)	(1.73)	(1.85)	(1.48)
Log market size	0.010**	0.005*	0.004*	0.004*	0.004*
	(2.13)	(1.83)	(1.66)	(1.67)	(1.68)
Log firm size	0.036***	0.023***	0.019***	0.018***	0.016***
	(7.12)	(5.33)	(4.84)	(5.05)	(5.28)
Firm age	0.000	-0.001	-0.002	-0.001	-0.001
	(0.05)	(-0.49)	(-0.65)	(-0.47)	(-0.29)
Log price	-0.009*	-0.008*	-0.008*	-0.007**	-0.007**
	(-1.79)	(-1.73)	(-1.85)	(-1.98)	(-2.21)
Constant	-0.522***	-0.266***	-0.186***	-0.176***	-0.161**
	(-4.51)	(-3.38)	(-2.67)	(-2.65)	(-2.54)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	2410	2410	2410	2410	2410
R^2	0.620	0.679	0.690	0.685	0.691
Adjusted R^2	0.575	0.641	0.653	0.648	0.654
Clustered by	Firm	Firm	Firm	Firm	Firm

The positive relationship between HFT and stock price informativeness weakens in magnitude and remains statistically significant only for the first two horizons in stable economic conditions. This means that HFTs' positive effect is even stronger when crisis years are taken into account. Thus, the positive effect is unlikely to be driven by economic uncertainty because economic crises generally erode price informativeness as shown earlier. The results in Table 8 indicate instead that HFT enhances stock price informativeness, particularly in crises. Yet, the improved price informativeness could result from the general improvement in market conditions after a crisis subsides and the economy starts to recover. However, if the positive effect would result from the post-crisis economic upturn, the effect should be larger when crisis years are omitted and not vice versa as the results in Table 8 suggest. Hence, these results do not support the rationale that the positive price informativeness effect would be driven by the post-crisis expansion.

The differing economic states between these markets at the time of HFT entrance could still impose to biases in staggered DiD design. This is because when HFTs entered the market first in Sweden and Norway during a stable economy in 2005 and later in Denmark and Finland during the financial crisis in 2008, the first-treated and later-treated control groups systematically differ from one another at the time of treatment which could distort the coefficients.

Fama and French's (1993) three-factor model states that small stocks tend to be riskier and less resilient in economic crises. Therefore, the cross-sectional tests between small and big companies are re-run without crisis years to see if these groups are affected any differently by HFT presence in purely normal times and whether the results in Table 8 apply to both groups. Results in Table 9 show that the coefficient difference between small and big companies is economically and statistically less significant when crisis periods are excluded from the estimation. The average coefficient difference between small and big companies drops from 0.012 (Table 5) to only 0.0066 coefficients when crisis years are omitted. This equals roughly a 45% drop in the average coefficient difference between large and small firms. The coefficient difference is also statistically less significant in every horizon as it drops from the 1% level to only 10% level. This sharp decline in the coefficient difference is mainly driven by the coefficient change in small stocks whereas big stocks remain nearly unaffected by the HFT entrance as in the original cross-sectional test. The average HFT coefficient on small stocks declines from 0.014 (Table 5) to 0.0086 which equals around a 39% reduction in the HFTs' coefficient effect on small stocks. HFTs' average coefficient effect on large stocks grows slightly from 0.0016 (Table 5) to 0.0018, but the effect remains statistically insignificant.

Table 9. Cross-sectional tests between small and big companies excluding crises.

This table presents the coefficients of cross-sectional tests between small and big firms where the HFT dummy is regressed on price informativeness measure for each one to five-year horizon (h) while crisis years are excluded. Log market size, firm age and log price serve as control variables. Year and firm fixed effects are included, and standard errors are clustered at the firm level. T-statistics are given in the parentheses. ***, ** and * signify statistical significance at 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Priceinfo	h = 1	h = 2	h = 3	h = 4	h = 5
Small firm (d)	-0.027***	-0.017***	-0.014***	-0.014***	-0.013***
	(-3.65)	(-3.10)	(-2.94)	(-3.11)	(-3.21)
Big firm (d)	0.027***	0.017***	0.014***	0.014***	0.013***
	(3.65)	(3.10)	(2.94)	(3.11)	(3.21)
HFT x small firm	0.013**	0.010***	0.007**	0.007**	0.006**
	(2.36)	(2.65)	(2.16)	(2.25)	(1.97)
HFT x big firm	0.004	0.003	0.001	0.001	0.000
	(0.73)	(1.02)	(0.35)	(0.50)	(0.19)
Coeff. difference	0.009*	0.007*	0.006*	0.006*	0.005*
	(1.67)	(1.79)	(1.86)	(1.84)	(1.82)
Log market size	0.013***	0.008**	0.006**	0.006**	0.006**
	(2.75)	(2.49)	(2.25)	(2.23)	(2.18)
Firm age	0.002	-0.000	-0.001	-0.000	0.000
	(0.56)	(-0.03)	(-0.25)	(-0.07)	(0.09)
Log price	0.008**	0.003	0.002	0.001	0.001
	(2.03)	(1.03)	(0.56)	(0.56)	(0.40)
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Observations	2410	2410	2410	2410	2410
R^2	0.577	0.649	0.665	0.661	0.669
Adjusted R^2	0.526	0.608	0.625	0.621	0.630
Clustered by	Firm	Firm	Firm	Firm	Firm

The results in Table 9 show that HFT presence enhances the price informativeness of small stocks in a stable economy whereas large stocks remain unaffected. Yet, the positive effect on small stocks is smaller compared to the overall sample that includes crisis periods as well. This suggests that HFT presence improves the price informativeness of small stocks, not only during normal times, but especially in uncertain economic circumstances. Hasbrouck and Saar (2013) discover that HFTs begin to trade small stocks in volatile market conditions which supports this interpretation. They propose that large price movements provide a profitable environment for HFTs where even small illiquid stocks may turn to potential HFT investments. Aït-Sahalia and Brunetti (2020) controversially state that HFTs cut back their trading during high volatility since they pursue to gain from subtle price changes. Overall, the views are divided regarding HFT behaviour during volatile market conditions. Some studies suggest that HFTs reduce short-term volatility by continuing to trade against transitory pricing errors and supplying liquidity during uncertainty (Aït-Sahalia & Brunetti, 2020; Brogaard et al., 2014; Hagströmer & Nordén, 2013; Hasbrouck & Saar, 2013). Whereas others suggest that severe volatility may cause HFTs to decrease their liquidity supply or even shift to aggressive liquidity consuming trades while repelling other liquidity suppliers with additional adverse selection costs (Aït-Sahalia and Brunetti, 2020; Brogaard et al., 2019; Jain et al., 2016).

To conclude, HFTs' effect on the price informativeness of large corporations remains insignificant regardless of the economic state. Stock prices of small companies, on the other hand, become more informative when HFTs enter the markets and this positive influence is emphasised in stressful market conditions. These results suggest that HFTs most probably continue to provide liquidity to small stocks and potentially even increase their trading of small stocks in crises. Thus, this could explain HFTs' more significant effect on small stocks and the overall improvement in stock price informativeness during economic downturns.

7 Conclusions

HFT has globally revolutionized the functioning of modern equity markets and its effects on market efficiency have sparked wide debate in market microstructure research. Current HFT research mostly focuses on the U.S. market stating that HFT enhances short-term price discovery while studies concerning far-reaching effects on stock price informativeness are yet slim. Weller (2018) is the first to propose that the millisecond improvements in the price discovery of already existing information are realized at the expense of information acquisition. The acquisition of new information is vital in achieving fundamentally reliable stock prices that reflect the long-term profitability of a company. This enables the optimal allocation of finite resources and thus the maximum prosperity in the society.

HFTs have significant influence also in the Nordic markets where they cover up to half of the trading volume. This thesis provides novel insight into how stock price informativeness about future cash flows evolves in one to five-year forecasting horizons after HFTs enter the Nordic stock markets. The staggered DiD tests produce statistically significant results indicating that one standard deviation of HFT increases long-term price informativeness by 7% on average. The positive effect is strongest for the two first horizons, after which it declines for further horizons. These results contradict previous HFT studies by showing that stock prices become slightly more successful estimates of future cash flows after HFTs enter the Nordic markets. However, the robustness of these results cannot be conclusively proven since no significant change is observed in price non-synchronicity.

The cross-sectional tests show that small stocks experience larger growth in price informativeness relative to large stocks which are unaffected by the HFT presence. This deviates from the prevailing view in HFT research, according to which HFTs tend to trade large liquid stocks over small stocks. This raises concerns about whether the effect is truly driven by the HFT presence or whether some other confounding factors such as ETF share, institutional holdings or market microstructure could contribute to these deviating results. Prior studies show that ETF market share is negatively associated with stock price informativeness and that institutional investors prefer large stocks, so these factors are unlikely to explain the positive informativeness effect on small stocks. Market fragmentation furthers the liquidity and price efficiency of large stocks but has the opposite effect on small stocks. The distinctive factor compared to previous studies is that Nordic markets are considerably less fragmented than other markets which could cause abnormal HFT behaviour in the Nordic exchanges of this thesis. Hence, liquidity supplying HFTs can set thinner spreads and choose to trade small stocks more often in Nordic markets compared to other more fragmented markets where liquidity suppliers face higher adverse selection risk. Lower fragmentation also offers fewer arbitrage opportunities which could explain why large stocks remain unaffected by the HFT presence. No significant difference is detected among young and old companies after HFT entrance.

This thesis also addresses the possible contribution of financial downturns because HFT entrance in Denmark and Finland coincides with the financial crisis in 2008. The results remain close to unchanged when economic crises are controlled in the price informativeness estimation. However, when crisis periods are excluded from the sample, HFTs' positive effect on price informativeness declines by one third on average. This change is driven by small stocks while large stocks remain unaffected. The positive informativeness effect is unlikely to be driven by economic crises because price informativeness evidently decreases during uncertainty. Instead, these results propose that HFT presence enhances price informativeness of small stocks in normal times but even more so in economic downturns. This indicates that HFTs not only continue to provide liquidity to small stocks, but they might even increase their trading of small stocks during high volatility.

Results in this thesis show that HFT presence enhances stock price informativeness regarding future cash flows in the Nordic markets, challenging the prevailing view that HFT would unambiguously hamper long-term price informativeness. This thesis suggests that HFTs' positive contribution to short-term price discovery exceeds the potential drawbacks in the acquisition of new information. The fundamental information is incorporated into prices more effectively after its public disclosure and thus share prices correspond more closely with companies' long-term success. In the end, only public information has social value as it determines production and investment decisions. HFT algorithms also react to public information without humane limitations or irrationalities which can impose persisting deficiencies on price informativeness.

It should be noted that the results of this thesis are based on a trend of HFT presence, and the causality between HFT presence and increased price informativeness cannot be demonstrated. Yet, the possibility of reverse causality can be ruled out because the positive price informativeness effect is solely observed among small stocks. Furthermore, closely staggered time-varying HFT treatment combined with two-way fixed effects could potentially expose to omitted common trends or creditability issues. Thus, more empirical attention is required to form a consensus regarding HFTs' contribution to long-term price informativeness. Extending future research to less studied markets and including more efficient statistical tools in processing massive HFT intraday data would enable proving causality and recognising the mechanisms between HFT behaviour and price informativeness.

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Appendices

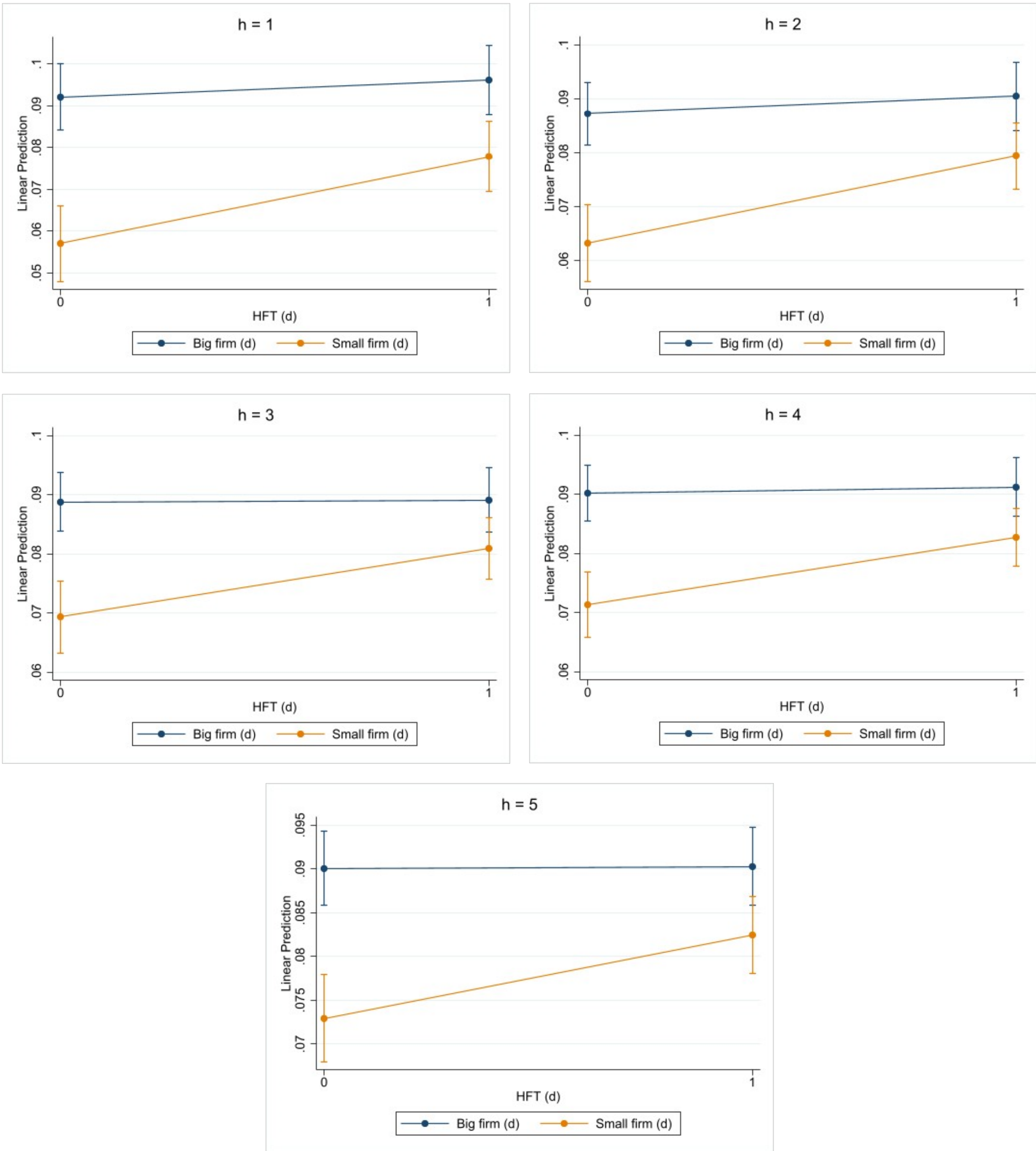
Appendix 1. Variable definitions

This table provides definitions for the variables used in the estimations.

Variable	Definition
Price informativeness measures	
Priceinfo	Future earnings are regressed on current market prices in each year and horizon through one to five years. The resulting forecasting coefficient is multiplied by the cross-sectional standard deviation of the natural logarithm of market capitalization scaled by total assets. The priceinfo measure is the forecasted variance of future earnings from current stock prices.
Nonsynch	The firm-specific return residual that is unexplained by the asset pricing factors. It is obtained by scaling the firm-specific return variance with the overall stock return variance.
Market factors	
Consumer Price Index (CPI)	The weighted average price change of a basket consisting of consumer goods and services.
HFT (d)	A dummy variable that is zero before HFTs enter the market and one after.
Crisis (d)	A dummy variable that is one if the annual return of a market index is -10% or less and zero otherwise.
Gross Domestic Product (GDP)	The market value of all the goods and services produced in a given market.
Market size	The total market capitalization value of all listed companies in a given market.
Company factors	
EBITDA	A cash flow variable that indicates earnings before interest and taxes.
Market capitalization	A company's share price at the end of the fiscal year multiplied by the total number of its outstanding shares.
Total assets	A company's current and long-term assets.

Appendix 2. Predictive margins of small and big firms

The predictive margins of HFT treatment effect on small and big companies with 95% confidence intervals in one to five-year horizons.



Appendix 3. Predictive margins of young and old firms

The predictive margins of HFT treatment effect on young and old companies with 95% confidence intervals in one to five-year horizons.