Henrik Järvinen

The Impact of High-Frequency Trading on Stock Market Efficiency

School of Accounting and Finance
Bachelor's Thesis, Finance
Accounting and Finance

Vaasa 2025

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Henrik Järvinen
Title of the thesis: The Impact of High-Frequency Trading on Stock Market Efficiency
Degree: Bachelor of Science in Economics and Business Administration
Discipline: Finance
Supervisor: Anupam Dutta
Year: 2025 **Pages:** 33

ABSTRACT :
The purpose of this thesis is to examine the impacts of high-frequency trading on stock pricing and the role it has in enhancing or undermining market efficiency. The study focuses on both the corrective and disruptive roles high-frequency trading plays in modern financial markets.

How high-frequency traders impact market efficiency has been a debate globally in financial literature. Classical theories in finance suggest that markets are efficient, where stock prices reflect all available information. Advanced algorithms and strategies used by high-frequency traders can influence market outcomes in multiple ways and previous research on high-frequency trading suggests that it can both enhance market efficiency and undermine it through its actions.

Financial literature portrays high-frequency traders as a highly informed market participant group, that uses advanced technology to gain an edge in the equity markets. Previous research supports that high-frequency traders contribute to price efficiency by rapidly incorporating information into stock prices. However, there are also various studies providing evidence of the inefficiencies created or amplified by high-frequency trading.

KEYWORDS: Not defined yet

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1 Introduction

High-frequency trading (HFT) is a highly sophisticated subset of algorithmic trading that has greatly reshaped modern financial markets. At its core, HFT uses advanced algorithms and high-speed data transmission to execute trades at lightning-fast speeds and this way enables high-frequency traders to respond to events at a speed, which is 100 times faster than a human can blink his eyes (Hasbrouck and Saar, 2013). HFT sets itself apart from traditional and conventional investing by its lightning-fast trading activity.

Since high-frequency trading is a relatively new phenomenon in the stock markets around the globe and its trading strategies are heterogenous, the exact definition of high-frequency trading is not universally agreed upon. The term “high-frequency trading” does not have a regulatory or legal definition and researchers have stated that defining and differentiating high-frequency trading based on publicly available data would be exceedingly hard. (Congressional Research Service, 2014.)

High-frequency trading can have a significant influence in the global stock markets and affect key market aspects from liquidity to price discovery and the overall stability of the markets (Virgilio, 2019). Therefore, it is very important to evaluate the ways through which high-frequency trading can impact these areas and if the potential benefits of it outweigh its potential drawbacks. Furthermore, should the presence of high-frequency traders be viewed as positive development for financial markets or rather as a cause for concern that might require regulatory action? Jones (2013) states that regulation has played a clear role in shaping the current automated market structure and future regulatory policies will continue to influence the trajectory of technological advancements in trading.

In this thesis, I draw on existing literature and empirical evidence to provide an analysis of high-frequency trading’s role in modern stock markets and address whether the benefits outweigh its controversial practices and potential drawbacks for other market participants. By addressing the dual aspects of high-frequency trading, this study aims to provide a perspective on the implications for the broader financial markets.

1.1 Purpose of the study

The purpose of this thesis is to examine the impact of high-frequency trading on stock market efficiency. Stock markets have for a long time relied on arbitrageurs to exploit and eliminate arbitrage opportunities to ensure that prices better reflect their instrinsic values. Technological advancements have enhanced arbitrage efficiency, which is expected to improve overall efficiency of the market in the long run. Accordingly, the first hypothesis is:

H1: High-frequency trading improves stock market efficiency in the long run.

High-frequency trading has faced a lot of criticism for its usefulness and the way it negatively impacts the short-term efficiency of the market. The negative impacts of HFT include for example: increased volatility, temporary price distortions, and raised costs for other market participants. The speed and technological advantages of high-frequency traders enables them to exploit other slower market participants and this leads to increased inefficiencies that would not exist without high-frequency traders. Therefore, the second hypothesis is:

H2: High-frequency trading increases short-term stock market inefficiencies.

These two hypotheses may seem to conflict at first but should not actually be exclusive in real-world markets. If high-frequency trading enhances long-term market efficiency through arbitrage and improved price discovery, it can at the same create short-term disruptions, such as increased volatility and price distortions. These potential short-term inefficiencies can be a byproduct of the process, that over time drives more accurate pricing and increased efficiency in the markets. This perspective sees the possible dual role of high-frequency trading in stock markets, where its short-term drawbacks are a mandatory part of its contribution to broader long-term benefits for all market participants.

These hypotheses are based on existing literature and prevailing perspectives on high-frequency trading, many of which highlight its dual impact on stock market efficiency. The motivation is to investigate the balance between these two opposing effects and their implications for the overall market efficiency.

1.2 Structure of the study

The first chapter outlines the purpose of this study and introduces the hypotheses. Chapter two defines high-frequency trading and its key characteristics. Chapter three examines the Efficient Market Hypothesis, the Random Walk Theory and the event study method. After that, related literature is covered in chapter four. Finally, chapter five summarizes the findings and presents the conclusions of the study.

2 Defining High-Frequency Trading

High-frequency trading is a subset of algorithmic trading and is characterized by very high speeds, very high turnover rates and very high order-to-trade ratios. High-frequency traders utilize high-frequency data with electronic trading tools to trade assets with computer programs that execute trades automatically without any human intervention. There is not a universally agreed definition of what high-frequency trading specifically is, but The Securities and Exchange Commission define high-frequency traders as “Professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis.” (SEC, 2014.)

2.1 Characteristics of High-Frequency Trading

The Securities and Exchange Commission’s initial definition of HFT is somewhat broad, so the SEC also identified five specific characteristics to provide greater clarity. The first one being that high-frequency traders use extraordinarily high-speed in addition with very sophisticated computer algorithms for generating, routing and executing their orders. (SEC, 2014.) For instance, some HFT firms transmit data via microwave networks instead of traditional fiber optic cables, as microwaves can transfer data approximately 30% faster, offering them a speed advantage. (Shkilko & Sokolov, 2020.) This reliance on advanced technology sets HFT apart from traditional retail trading, as the speed and complexity of HFT operations far exceeds what is achievable through conventional trading strategies and tools.

Another description of HFT given by the SEC involves traders using co-location services and data feeds provided by stock exchanges to minimize their network and processing latencies (SEC, 2014). Co-location allows traders to place their servers within the exchange’s data center, which significantly reduces latency, the time it takes to execute trading decisions. This setup enables high-frequency traders to adjust their quotes more quickly than those without co-location. (Frino et al., 2013.) This increase in speed is due to the shorter physical distance between the servers and the data center, which allows faster data transmission.

The SEC also notes that high-frequency traders operate with exceptionally short time frames for establishing and liquidating positions. While the duration for holding positions can vary among all market participants, HFTs are distinguished by their consistently brief holding periods. Hagströmer and Nordén (2013) highlight in their research that HFTs typically maintain positions for mere seconds or in some cases for only fractions of a second, which shows their reliance on very rapid market activity to generate profits. This characteristic of HFT reveals the high-speed and automated nature of HFT strategies that prioritize swift entry and exit from trades with minimal exposure to market risks. This behaviour of HFT is in stark contrast to the longer holding periods typical to traditional retail investors.

The SEC's fourth characteristic of high-frequency traders highlight their practice of submitting numerous orders, many of which are cancelled shortly after submission. This behaviour is quantified and measured by the order-to-trade ratio. Orders include new submissions, amendments, and deletions of existing orders. In general, High-frequency traders have a significantly higher order-to-trade ratio compared to other market participants. For example, the Australian Securities & Investment Commission reported that from May to July 2012 approximately 7% of HFTs on the Australian Securities Exchange operated at an order-to-trade ratio of 50:1 and some even exceeding 1000:1 (ASIC, 2013). Order-to-trade ratio (OTR) can be calculated as follows:

$$OTR = \frac{Number\ of\ Orders\ Submitted}{Number\ of\ Trades\ Executed} \tag{1}$$

The final characteristic of high-frequency trading identified by the SEC, is that HFT's end the trading day in a position as flat as possible. This means that the traders close out their open positions before the market closes and ensures that they do not carry trades overnight. By doing this, the HFT's limit their exposure to market risks that could arise from holding securities when the markets are closed. In a study of high-frequency trading by Baron et al. (2012), one of their definitions for HFT's were that their end of the day position ought to be no more than 5 % of their total daily volume. This focus on maintaining a nearly flat position by the end of each day underscores the short-term approach that defines high-frequency trading and distinguishes it from traditional investing. The formula for defining a high-frequency trader based on the study by Baron et al. (2012) regarding end of the day position can be expressed as follows:

$$\frac{P_{EOD}}{V_{DAILY}} \leq 0{,}05 \tag{2}$$

Where P_{EOD} denotes the end of the day position: the absolute value of the net position held by the trader at the close of the trading day. V_{DAILY} denotes the total daily trading volume: the sum of all buy and sell trades executed by the trader throughout the day. Threshold $\leq 0{,}05$: for a trader to qualify as an HFT under this definition, their end-of-day position must not exceed 5% of their total daily trading volume.

2.2 Types of High-Frequency Traders

High-frequency traders do not all follow the same trading strategies. In fact, there is not a single strategy that is followed by most of them. However, HFT's can be differentiated into three different main brackets based on their trading strategies. The first one being a market-maker that provides liquidity by placing both buy and sell orders continuously and profiting from the bid-ask spread. The second a group is made of relative-value traders that exploit pricing inefficiencies between related securities. Lastly, the third group consists of directional high-frequency traders that execute trades based on signals such as market news or order flow signals. (Jones, 2013.)

2.2.1 Market makers

A market maker is a financial intermediary that is ready to trade either side of the market and is involved in most securities transactions. A market maker maintains a two sided-auction and is ready to buy securities at the bid price they have set and sell at the ask price they have set from their own account (O'Hara & Oldfield, 1986). As stated by Roncella and Ferrero (2021), market making is to provide liquidity between buyers and sellers at times where there is no temporal match to maintain the market in an orderly fashion, since a good level of liquidity is needed for the proper functioning of the market.

The market maker needs to create a profit for constantly providing liquidity on the market and does that by charging a fee for taking the opposite side of a transaction. This fee is in the form of the bid-ask spread. The bid is the price at which the market maker will the buy securities and the ask is the price at which the market maker will sell the securities to other market participants. The market maker creates a profit for himself from the usually small difference between the bid and the ask price of a specific security, known as the bid-ask spread. (Logue, 1975.) Roncella and Ferrero (2021) explain that market-makers provide their service with their willingness to transact with other market participants, but simply the only important intention to them is to maximise their own profits.

As the types of investors and investments strategies have changed under time, market makers have also evolved. Menkveld (2013) demonstrates that high-frequency trading has made market making more efficient, thus HFT firms have now taken over market activity in this specialized role and replaced the old traditional market makers. Bellia (2017) also states that the old class of market makers have vanished and a more modern version of market makers that make use of high-speed connections, co-location and fast computers have taken their place in the markets.

Investors want to trade securities with minimal transaction costs and a narrower bid-ask spread lowers the costs for them. Hence, market makers need compete with each other to provide a bid-ask spread that is as narrow as possible to attract other market participants to use their services. Verousis et al. (2017) show that the small tick sizes in modern markets allow high-frequency traders to better implement their strategies than traditional market-makers lacking the capabilities for high-frequency trading. As HFT’s can provide market-making services more efficiently than traditional market-makers, this is a strategy widely used by HFT’s.

2.2.2 Relative-Value High-Frequency Traders

Relative-value trading is one of the most common quantitative trading strategies used by a variety of hedge funds and investment banks. Relative-value trading falls under the category of statistical arbitrage, a form of speculative trading that relies on the historical correlation between different assets. For example, if two stocks have historically moved together, it can be reasonably expected that their correlation will also hold in the future. When the spread between these two stocks widens, a trader would make a profit by buying the loser and shorting the winner, then closing the position when the prices have converged in the future. Relative-value trading makes profits by utilizing market inefficiencies and the risk adjusted returns from it should not be positive if the markets were always efficient. (Gatev et al., 2006.)

Relative-value trading is simple in theory, but the practical implementation of it is more complex. Market frictions such as transaction costs, taxes and financing costs make the strategy more challenging to execute profitably in practice. Additional factors like identifying suitable securities, managing stable relationships and monitoring spreads complicate the succesfull execution of relative-value trading even more. Furthermore, even without taking these factors into consideration, relative-value trading is not pure arbitrage and carries risk since it is only a strategy that relies on mathematical models calculated from historical data. (Nath, 2003.)

Relative-value trading dates back to 1980's at Wall Street and has been popular ever since. It has been appealing due to it being market neutral, as a trader holds a simultaneous long and short position, making the strategy not influenced by the overall direction of the market (Miao, 2014). Gatev et al. (2006) note that automated trading systems take intuition and a traders individual skill out of the arbitrage and replace it with consistent filter rules. Miao (2014) further demonstrate that HFT have decreased the holding periods of these relative-value arbitrageurs from weeks to minutes or seconds and therefore increased the frequency of profits. This explains why technological advancements such as HFT systems have made relative-value trading more efficient and the reason why HFT's have taken over this field from human traders.

2.2.3 Directional High-Frequency Traders

While relative-value arbitrage relies on price convergence, directional high-frequency trading is based on the theory that there are predictable price movements due to events, such as financial news or price-movements that predict the future short term price direction of an asset. Foucault et al. (2015) state that modern financial markets have an almost continuous flow of news. This flow of news includes quote updates or trades on the market as well as information that can be machine-read and analyzed such as economic news, corporate reports or even Facebook posts. Because of this very diverse and rapidly available data, directional trading has become a commonly used strategy by high-frequency traders, since their algorithms can process and react to data far more quickly than humans traders can.

The (SEC, 2014) report provided a broad definition of directional strategies and described them as the practice of establishing positions in anticipation of future price movements, primarily with the use of aggressive, marketable orders. Schneiderman et al. (2014) argued that HFT's do not even care about the accuracy of new information and the only thing that matters is, if the information will impact the market or a security. And because HFT's will be out of their position in milliseconds they are not conserned with the long-term effects of new information, focusing only on the short-term price impact that will make them immediate profits.

HFT firms are electronically applying textual analysis for new information and trading based on this data. Jones (2013) demonstrate that this textual analysis is sometimes done by searching for specific keywords in a text like "increased" or "raised" near a term such as "earnings forecast". These algorithm programs then determine how to act upon the information and buy or sell shares based on these words in milliseconds. As a result, this swift and automated trading enables HFT firms utilizing textual analysis to gain a competitive edge against human traders and make a profit by reacting to new information faster than all other market participants.

3 Market efficiency

There has been considerable debate regarding whether HFT is beneficial for all market participants and studies have been done to either support or challenge this hypothesis that HFT improves market efficiency. Some contend that HFT has a positive effect for the overall market efficiency, while critiques argue that HFT only impacts market efficiency negatively rather than enhancing it. Fleeting market inefficiencies are also precisely what high-frequency traders desire and seek to capitalize on, using their superior speed and technology to make a profit from even the smallest price discrepancies.

To analyse the role of high-frequency trading in influencing stock market efficiency and price behaviour, the theories about market efficiency and price behaviour ought to be covered. Numerous theories in financial literature try to explain how markets incorporate information into asset prices. Efficient Market Hypothesis and Random Walk Theory being two of the most prominent theories in financial literature. This section examines these two important and closely related market efficiency theories. The section also covers event studies, which are used to test market efficiency.

3.1 Efficient Market Hypothesis

Eugene Fama introduced the Efficient market hypothesis (EMH) in the 1960’s, where he proposed that financial markets are efficient in a way, where asset prices fully reflect all of the available information at any given time. According to the theory, it ought to be impossible for investors to consistently outperform the market, either through stock picking or market timing. This is because all the information is accurately incorporated into the stock prices and also because any random event in the future cannot be predicted by anybody. According to the theory, whenever inefficiencies in stock prices do occur, arbitrageurs will quickly take advantage of these opportunities and drive the prices back to their correct values, eliminating the inefficiencies.

The Efficient Market Hypothesis comes in three different forms. These are the weak form, the semi-strong form, and the strong form. According to the weak form, stock prices reflect only the historical price data and trading volumes. The semi-strong form suggest that stock prices incorporate all publicly available information, such as financial reports, earnings announcements and economic news. The strong form of EMH argues that stock prices fully reflect all information, both public and also private. Suggesting that, even revealing insider information would have no impact on stock prices, since it is already reflected in the prices by all market participants. (Fama,1970.)

The EMH is built on several key assumptions that do not always hold true in real world markets and makes it therefore mainly a theoretical model. It assumes the financial markets to be completely frictionless, which means that there are no transaction costs or other barriers for trading. Furthermore, it requires that all information is readily and freely available for all participants and also, that investors uniformly interpret this information and its implications for current and future asset prices. Finally, the EMH requires all market participants to always act rationally, so that irrationality among market participants would not cause any discrepancies in the prices. (Fama,1970.) These are just a few of the assumptions in the Efficient Market Hypothesis, highlighting its limitations in practical application.

3.2 Random Walk Theory

The Random Walk Theory is closely linked to the Efficient Market Hypothesis as both theories suggest that stock prices fully reflect all available information. The random walk theory states that stock price changes are independent and identically distributed random variables. According to this theory, past price movements will not provide insight into future prices and therefore predicting future stock prices based on past price movements ought to be impossible. This means that price changes have no memory and aligns closely with the efficient market hypothesis. Both of these theories suggest that in an efficient market, all known information is already reflected in asset prices which leaves no room for consistent prediction or arbitrage opportunities. (Fama, 1995.)

Fama (1995) notes that the random walk model assumes that past price movements contain no information about future prices and therefore being able to identify exploitable trends ought to be impossible. Just as with the EMH that is built on some unrealistic assumptions, the random walk model is also a theoretical model which does not always hold true in the real world. Virgilio (2019) demonstrates that many HFT strategies would become unviable if the random walk hypothesis were literally true in real world markets because many HFT strategies depend on the existence of temporary market inefficiencies or detectable patterns. These inefficiencies or detectable patterns would not occur in a market adhering strictly to the random walk hypothesis.

Lo and MacKinlay (1988) argue that while markets often exhibit characteristics of randomness, certain predictable patterns, such as momentum or mean reversion, can emerge because of market participants' behaviour or structural inefficiencies in the market. In addition, Grossman and Stiglitz (1980) state that if markets were entirely efficient and random, there would be no incentive for any trader to gather and act on information, as no profits could be derived from this. Studies show that while the random walk hypothesis forms a valid theoretical framework, real-world markets often deviate from its assumptions and create opportunities for market participants to create sophisticated trading strategies to exploit these inefficiencies.

$$P_{t+1} = P_t + \epsilon_t \tag{3}$$

The random walk model can be expressed in a very simple way as a mathematical formula as follows. P_t is the stock price at time t and P_{t+1} is the stock price at the next time step. ϵ_t is a a random variable representing the unpredictable change in price, whis is assumed to follow a normal distribution with mean zero and a constant variance. This simplified formula provides a useful approximation of stock price behaviour, while assuming a constant variance.

In real world markets the variance is not actually a constant and fluctuates based on market conditions. As demonstrated by Virgilio (2019) and Lo and MacKinlay (1988), certain detectable patterns in the market exists. Easily detectable patterns are periods of high volatility that are followed by more volatility and periods of low volatility that tend to also persist. This phenomenon is referred to as volatility clustering. (Ning et al., 2014). More sophisticated models such as GARCH (1,1) by Bollerslev (1986), therefore exist that take into account the time-dependant variance. This model is widely used in finance and economics and takes into account the fact that future volatility depends also on past volatility. This model can be expressed as follows:

$$\in_t = \sigma_t Z_t \; ;$$
$$with\ \sigma_t^2 = \omega + \alpha \in_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

The first part of this simplified GARCH (1,1) formula refers to the innovation at time t, where $\in_t$ represents the asset return shock, σ_t is the time-varying volatility and Z_t is a white noise process that is typically assumed to follow a standard normal distribution $Z_t \sim N\,(0, 1)$. This ensures that returns exhibit randomness with a time-dependent variance. (Bollerslev, 1986).

In the second part of the equation σ_t^2 represents the conditional variance of stock returns at time t that depends on three components: $\alpha \in_{t-1}^2$, which captures the impact of past squared return shocks. $\beta\sigma_{t-1}^2$ accounts for the influence of previous period variance and ω is a constant that represents the long-run baseline variance. This approach allows the model to take into consideration the persistence of volatility and makes it a tool for forecasting market risk and understanding price fluctuations. A high degree of continuation in volatility in the GARCH (1,1) model is detected, if $\alpha + \beta$ is close to 1. This means that volatility shocks have long-lasting effects, which can be observed on the stock market. (Bollerslev, 1986).

3.3 Event study

The event study methodology was developed by Fama et al. (1969) and this laid the foundation for testing market efficiency by analyzing how stock prices react to new information. Binder (1998) states that a revolution was started after the paper by Fama et al. (1969), as this event study methodology became the standard method of measuring how events and announcements impact security price behaviour. Announcements such as the earnings announcement contain information that should impact the pricing of a stock and the event study method can be used to measure if the market efficiently incorporates that information.

The event study methodology has ever since been widely applied in research to assess how quickly and accurately stock prices adjust to any new information. MacKinlay (1997) demonstrates that event studies rely on calculating abnormal returns. The abnormal returns measure the difference between the actual stock return and the expected return in the absence of a particular event, such as earnings announcement. This event study method allows to test if the markets react instantaneously and correctly to new information and aligns with the predictions of the Efficient Market Hypothesis. The abnormal returns can be calculated as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t) \tag{5}$$

Where $\mathrm{AR}_{\mathrm{i,t}}$ represents the abnormal return for the stock i at time t, $\mathrm{R}_{\mathrm{i,t}}$ is the actual return for the stock i at time t and $\mathrm{E}(\mathrm{R}_{\mathrm{i,t}}|\mathrm{X}_{\mathrm{t}})$ denotes the expected return for the stock i at time t. and X_{t} represents the conditioning information for the normal return model. MacKinlay (1997) states two approaches for modelling normal returns. The first approach is the constant mean return model, where X_{t} is a constant, implying that a security's mean return stays constant through time. The second approach is the market model, in which X_{t} is the market return and assumes a linear and stable relation between the security return and the overall market return.

As HFT accelerates market reactions to news and announcements, since the algorithms can process and trade on new information in milliseconds (Brogaard et al., 2014). The rise of HFT has introduced a new dimension to event studies as researchers can now evaluate whether HFT contributes to market efficiency by comparing stock price reactions and behaviour before and after the rise of high-frequency trading. Through event studies, researchers can evaluate whether HFT is impacting market efficiency in a positive or negative way.

4 Impact of High-Frequency Trading on market efficiency

The impact of high-frequency trading on market efficiency has been a debated topic in financial literature. Many studies highlight the ways in which HFT has a positive impact on market efficiency, by for example improving liquidity, accelerating price discovery, and reducing mispricing of stocks. However, research also shows that the actions of HFT can have a diminishing effect on market efficiency, with negative consequences such as increased volatility, decreased liquidity and the exploitation of other market participants.

Since there is disagreement and differing perspectives on how high-frequency trading affects market efficiency, both the negative and positive impacts of it ought to be examined. This section reviews previous research on the subject to evaluate the overall impact of HFT on market efficiency.

4.1 Cross-Market and Index Strategies

The law of one price is a fundamental principle and a basic building block of financial economics which plays a significant role in the financial markets. The theory states that identical goods ought to have the same price in two or more competitive markets without transaction costs or trade barriers. The logic for why this principle should hold true in theory and also in real world markets is quite simple: if an asset is selling for different prices in two locations at the same time, then arbitrageurs will intervene to exploit the price discrepancy and profit from the imbalance, while restoring the price uniformity. (Lamont & Thaler, 2003).

According to the law of one price, the shares of a cross-listed company should trade for the same price in two different markets. Jones (2013) explains that a high-frequency trading strategy relying on this principle is referred to as cross-market arbitrage. High-frequency traders utilizing this strategy are trying to profit from the price difference of a share in different markets. This arbitrage conducted by high-frequency traders ensure that the same share trading for example in both New York and London maintains constant pricing across the two markets. Dodd et al. (2023) demonstrate that high-frequency trading activity significantly reduces the mispricing of cross-listed stocks between the US and Canadian markets.

The amount of high-frequency trading of a stock increases as the stock is cross-listed by opening a venue for cross-market arbitrage opportunity that high-frequency traders can exploit. Mispricing between the two markets is then significantly reduced by high-frequency trading activity on these cross-listed stocks. (Dodd et al., 2023). As stock mispricing decreases, market efficiency increases, allowing asset prices to more accurately reflect their intrinsic value. Jones (2013) states that while cross-market arbitrage has been practiced for decades, high-frequency trading has enhanced this process due to faster reaction times and lower costs of trading.

Index arbitrage is another strategy employed by high-frequency traders to create profits for themselves, while simultaneously improving market efficiency by ensuring that prices of related instruments remain aligned. An example of this can be made with S&P 500 Futures and (SPY) the ticker for the largest electronically traded fund tracking the S&P 500 index. These two instruments, while not being exactly identical, are so correlated that their prices should move in tandem. If the S&P 500 futures price increases without a corresponding increase in the SPY ETF at the same time, a high-frequency trader can exploit this price disparity by buying the SPY ETF and shorting the S&P 500 futures. When the prices realign, the trader closes both positions, capturing a profit from the temporary mispricing, which then vanishes because of the trader’s action. Hence, HFT traders contribute positively to market efficiency by profiting from temporary price discrepancies (Jones, 2013).

4.2 Price discovery acceleration

Price discovery is a building block of market efficiency, as it ensures that asset prices reflect all available information in a timely manner. Price discovery can be defined as the process by which the value of a specific security is established through market supply and demand dynamics. Price discovery is accelerated when new information is more rapidly incorporated into security prices. Putniņš (2013) state that the first market to reflect new information about the fundamental value of a security is considered to dominate the price discovery process. For example, if a stock trades on two different exchanges and a positive earnings announcement is released, the exchange that incorporates this information faster into the stock's price demonstrates dominance in price discovery.

Research paper by Brogaard et al. (2014) examines the impact of HFTs on price discovery and they find in their study that HFTs facilitate price efficiency with their strategies by trading in the direction of permanent price changes and against transitory pricing errors. Hence, it shows that HFT's trading behaviour contributes positively to the pricing of assets aligning with their fundamental values and not against them. Brogaard et al. (2012) further demonstrates that HFTs are actively participating in enhancing market efficiency by correcting mispricing and ensuring that market prices reflect all available information.

Furthermore, price discovery can also be accelerated without the need for executed trades by so called cancel clusters. Cancel clusters are a rapid burst of limit order cancellations by HFTs that are reacting to new information. Instead of requiring slow execution-based intermediate trades to adjust security prices, HFTs' cancellations update quotes almost instantly. This alignes the new bid and ask prices with the fundamental value of a security as quotes are adjusted rapidly in response to new information. This behaviour results in an accelerated price discovery process and price discovery through cancellations is also more efficient, since no money needs to change hands for the quotes to be updated. (Blocher et al., 2016.)

4.3 Legal front running

High-frequency trading has faced significant critisism for engaging in what some describe as legal front-running, often at the expense of large institutional investors. (Hens et al., 2017). Traditional definition of front running -buying stocks based on insider information of an upcoming large order- is illegal. Linton and Mahmoodzadeh (2018) define the traditional way front running has been usually done as: brokers in charge of executing an order for a client buying the shares for their own account and then selling them to the client at a higher price making a profit for themselves. HFT's however do not do exactly this, but are able to front run in a sligthly different and legal way.

Linton and Mahmoodzadeh (2018) compared HFT front runners to those who would buy an entire section of a sporting event and then selling the tickets to those who actually want to go the game for a higher price. At its core, HFT front-running involves removing liquidity and offering it back at a worse price. Using advanced algorithms and ultra-fast data transmission, HFTs can detect and react to incoming orders from other market participants before they are fully executed, enabling them to profit without violating current trading laws. This strategy involves removing liquidity through market orders and promptly providing liquidity at a less favorable price using limit orders. However, HFTs can only profitably execute this approach against market orders submitted by other market participants. When HFTs employ this strategy, it causes the original orders from other participants to be executed at less favourable prices (Hens et al., 2017).

High-frequency traders are not able to see customer orders before they go out to the market and deciding to illegally front-run them in the traditional way. However, HFTs can detect and respond to orders at the market with their fast access to market data and make a very short-term forecast of the future price of a stock with their algorithms to create profits for themselves. (MacKenzie, 2016c). This strategy enables HFTs to profit from buying and immediate reselling of the shares at a slightly higher price to the detriment of other market participants.

Co-location plays a significant role in enabling this front-running practice of high-frequency traders. HFT firms purchase server space within the stock exchanges data center and gain a competitive advantage with faster access to trade and quote information directly from the exchanges matching engine. This setup by HFT's creates an information asymmetry, disadvantaging other market participants while allowing co-located HFTs to execute orders more swiftly and to exploit market opportunities at the expense of others. (Hens et al., 2017). Hasbrouck and Saar (2013) note that with co-location, some HFTs can detect and respond to events like orders or bid changes and have their response executed by the exchange in less than two milliseconds.

4.4 Short term volatility

Zhang (2010) investigates the impact of HFT on stock price volatility in the U.S. equity markets. The study finds that stock price volatility is positively correlated with high-frequency trading activity. This correlation is strong especially on large-cap stocks that have high institutional ownership and during periods of market uncertainty. A one standard deviation increase in HFT activity raises stock volatility by 5,6 % and increases price reactions to earnings news by 8 % based on the findings of the study. Foucault (2015) further highligts that HFTs, with their faster access to news compared to traditional investors, contribute to increased stock market volatility and trading volume. These results support the view that HFT increases volatility and creates short-term price inefficiencies, since the market overreacts to fundamental news when HFT activity is high.

Similar results are found from a study by Caivano (2015), where the impact of increased HFT activity in the Italian equity market on stock-specific intraday volatility is examined. They conclude that higher HFT activity leads to significantly higher intraday volatility. The study reveals that a 1-standard deviation increase in HFT activity raises volatility by 0.5 to 0.8 standard deviations. Meaning that an increase of 10 percentage points in HFT activity increases the intraday volatility by 4 to 6 percentage points for pure HFT firms and by 3 to 5 percentage points when also including investment bank HFT desks in the calculations.

Bazzana and Collini (2020) analyse the impact of HFT using SPDR S&P 500 ETF data and find that HFT increases volatility particularly on high-volume trading days, while having a stabilizing effect on average volume days. However, they suggest that HFT should be differentiated into two different brackets based on their trading strategies when examining their impact on volatility: passive and aggressive. Passive HFT strategies feature the usage of limit orders that are posted on order books and aggressive HFT strategies use market orders, that can be immediately executed on the market. The study finds that aggressive HFT strategies consistently increase volatility, while in contrast passive HFT strategies reduce it.

Brogaard et al. (2014) analyse data from 120 randomly selected stocks on the NYSE and NASDAQ from years 2008 and 2009 to study the impact of HFT on market stability. Contrary to many other studies, their findings support that HFTs do not directly contribute to price instability, even during periods of high volatility and that they usually trade in ways that reduce transitory pricing errors. However, they conclude that actions by HFTs might indirectly increase volatility, and that it happens especially during times of market stress. The reason for this is that HFTs' superior technology and their faster market access enables them to exploit pricing inefficiencies, which then imposes adverse selection costs on non-HFT liquidity suppliers. This then leads to adverse selection costs on non-HFT liquidity suppliers, which might make them withdraw from the market and lead to more fragile markets and increased market volatility.

4.5 Flash crashes and market manipulation

Flash crashes are severe price changes that are abrupt and occur in an extremely short period. The most well-known flash crash happened on May 6th, 2010, when the U.S stock market experienced one of its most extreme price drops. The Dow Jones Industrial Average index dropped by nearly 9% in a single day, equivalent to 1010-points. In under five minutes the index experienced a rapid 900-point drop, before recovering most of these losses within 15 minutes. This event now known as "May 6th, 2010, Flash Crash" drew much attention to HFTs as media tried to uncover the reason for this absurd market disruption. (Golub et al., 2012).

Anvestigation into this flash crash was done by the Commodity Futures Trading Commission (CFTC) and Securities & Exchange Commission (SEC) because of its severity. The investigation concluded that this highly unusual event in the market did not happen because of a single market participant or organization but, as a result of activities by many market participants that fed on each other, creating a snowball effect. Altough the actions seemed to be unrelated, they caused a loop that created an extreme volatility spike in a short period of time. (CFTC & SEC, 2010).

Kirilenko et al. (2011) analyzed the flash crash and found its origins in an automated algorithm selling over four billion dollars' worth of E-mini S&P 500 June 2010 stock index futures contracts in a very short time period. This created an order imbalance that led to HFT's reaching their inventory limits after buying the security for some time and then quickly offloading their positions when liquidity was diminutive, contributing to the selling pressure. Moreover, HFT's utilizing cross-market arbitrage additionally contributed to this flash crash by for example selling stocks in the index and the SPY ETF and buying E-mini contracts during the crash.

Kirilenko et al. (2011) demonstrate that the actions of many market participants led to HFT's passing massive amounts of securities back and forth during the flash crash and they ended up transferring the selling pressure across US markets, significantly amplifying trading volume and market volatility. This highly unusual event initiated by the actions of an automated selling program therefore escalated into a systemic event that affected the entire U.S. financial market in a catastrophic way. The figure below illustrates the Dow Jones Industrial Average Index, S&P 500 Index and the E-Mini S&P futures on May 6, 2010. The data is presented at one minute intervals and demonstrates the steep decline, which is then followed by a very rapid recovery.

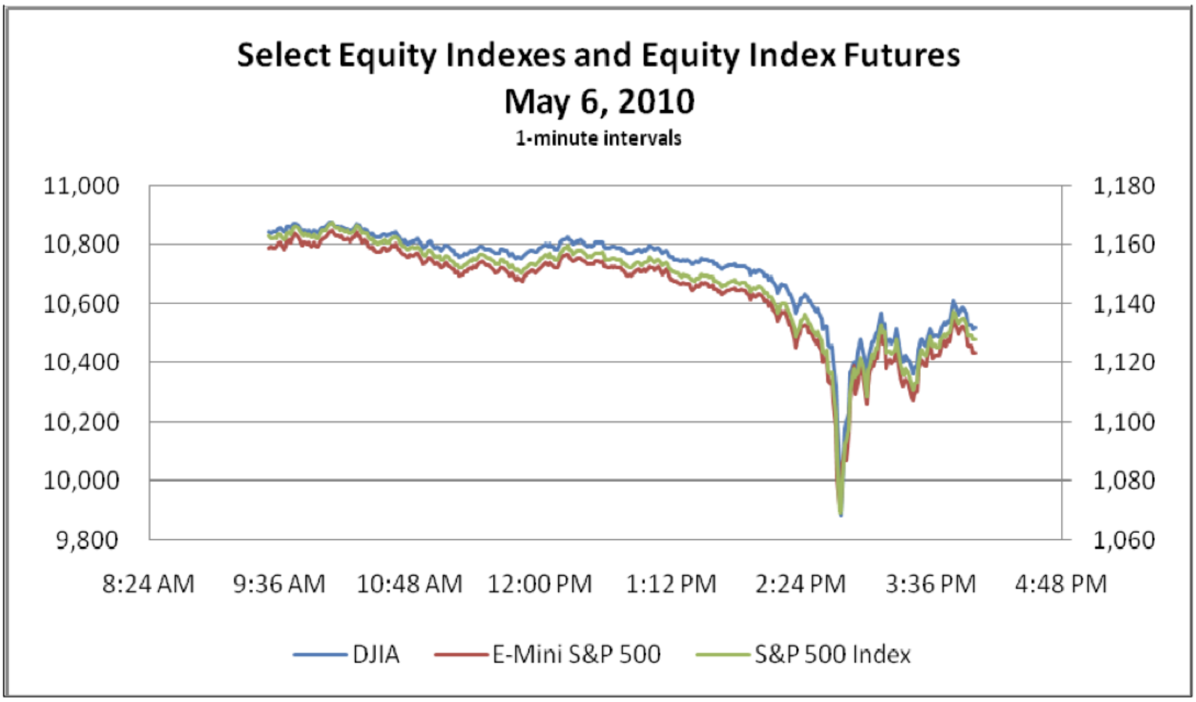

Figure 1. *May 6th. 2010 Flash Crash. (CFTC & SEC, 2010).*

(Johnson et al., 2013) analysed ultrafast extreme event data such as price spikes and crashes that occured within milliseconds from 2006 to 2011 from multiple stock exchanges. The study finds these events to be caused by high-frequency algorithms acting in unison and amplifying market instability. These ultrafast extreme events are not reactions to external news, but rather internal algorithmic interactions that show major deviation from regular movements in prices. (Serrano, 2020) and (Johnson et al., 2013) draw attention to the systemic risks of flash crashes and the instability caused by synchronized behavior among HFT's. They indicate the potential risks, as some of these events can escalate and lead to broad market instability. These studies higlight the need for deeper investigation into HFT's role in financial markets to better address the risks posed by these algorithm-driven trading systems.

5 Conclusions

This thesis examines the impact of High-frequency trading on market efficiency. Specifically, the disruptive and corrective roles High-frequency trading plays in modern financial markets. The thesis includes a section that explains what is classified as High-frequency trader and how they differ from other market participants. The concept of market efficiency is discussed before drawing on previous literature to address the hypotheses. The hypotheses in this thesis are based on previous literature and relevant studies are used to answer them.

Many studies suggest that HFT contributes positively to stock market efficiency by for example accelerating price discovery and minimizing pricing disparities across markets. High-frequency traders use strategies such as cross-market arbitrage and index arbitrage, and by doing this, ensure that stock prices align more closely with their intrinsic values and that price discrepancies are corrected swiftly. This continuous arbitrage process fosters a more competitive and efficient system for the stock market overall, and as such, these findings provide strong support for the first hypothesis that HFT improves long-term stock market efficiency.

Previous research aligns with the second hypothesis that high-frequency trading amplifies short-term stock market inefficiencies. Previous research on strategies used by high-frequency traders shows that HFT action can lead to overreactions in the form of increased market volatility and extreme events such as flash crashes. In addition to market overreactions, the exploitation of slower market participants by high-frequency traders often leads to adverse selection costs and has a negative effect on short-term market efficiency. While research supports that high-frequency trading contributes positively to long-term market efficiency, the short-term impact it creates often comes at a cost to other market participants and has a negative impact on the market stability.

The use of technological advancements has always provided an advantage to market participants that have leveraged them effectively. Technological innovations have evolved from carrier pigeons to telegraphs and finally to high-frequency trading. The current state of the stock markets globally has been shaped by these innovations that have been born from competition and ingenuity. It is also quite evident that high-frequency trading cannot be somehow un-invented or disregarded. That is why, it is important to study high-frequency trading further to better understand its impact on modern financial markets and to evaluate the necessity for potential regulations or other actions concerning HFT in the future.

Additional empirical studies are needed in the future to obtain more accurate results and conclusions regarding the impact of high-frequency trading. It is important to investigate the effects of high-frequency trading on the stability of the market and especially its impact during high volatility periods. How the actions of high-frequency traders can create systemic risk and how their strategies influence market dynamics ought to be studied more in the future to get results that will provide valuable answers. The effectiveness of existing regulatory measures should also be studied to mitigate potential current risks associated with high-frequency trading and to better understand the need for new frameworks to ensure fair and transparent market practices.

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