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Separating Truth and Myth in the Criticisms of High-Frequency Trading

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Abstract

This study delves into the existing literature on high-frequency trading and evaluates its impact on market quality, considering theoretical models and empirical evidence. Navigating diverse perspectives and regulatory intricacies, the research seeks to clarify high-frequency traders' influence on market dynamics, emphasizing both benefits and drawbacks. The findings contribute to a nuanced understanding of the high-frequency trader's role in equity markets, acknowledging its varied effects on liquidity, efficiency, and competition. Additionally, the study highlights potential policies and regulations to enhance the overall market.

Keywords

High-Frequency Trading, Algorithmic Trading, Financial Markets, Investment Strategies, Market Quality, Market Impact

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1 Introduction

The financial landscape is marked by a continual acceleration in both the gathering of information and the subsequent actions spurred by this information. Absolute speed holds significance for traders due to the inherent fundamental volatility of financial securities. Relative speed, denoting a faster pace than other traders, is equally crucial as it can create profitable opportunities through swift responses to news or market activity. This consideration appears to drive a competitive race wherein traders leverage cutting-edge technology and position computers in close proximity to trading venues to minimize order latency and secure a competitive advantage. Consequently, financial markets witness heightened activity in the millisecond environment, where computer algorithms interact at a pace 100 times faster than the blink of a human trader.

As traders invest in technology to process information more rapidly, the entire process of becoming aware of an event, analysing, generating trading signals and sending the order in has reduced to milliseconds, or in some cases, nano-seconds. The beneficiaries of this substantial technological investment seem to be a new category of traders employing high-frequency (HF) strategies, that respond to market events in the millisecond environment.

These traders now dominate quote activity in financial markets and, according to NASDAQ and the European Securities and Market Authority (ESMA), participate in the majority of trades. While there is an apparent increase in intermediated trading, with these HF traders serving as intermediaries, it remains unclear whether intense high-frequency trading (HFT) activity is detrimental or beneficial to the market.

In recent years, an area of examination has emerged, shedding light on the influence of HF traders on market dynamics. High-frequency traders, a specialized subset of algorithmic traders, operate on swift computing platforms, executing trades close to the spread while prioritizing risk aversion. Unlike traditional traders, the majority of HFT techniques aim to maintain net positions

close to zero at the end of each trading day and generally avoid influencing price movements.
Despite classical market microstructure models advocating for the beneficial impact of including HF traders in financial markets, the rapid order execution capabilities of HFT have raised varied opinions within the financial community about their impact on the market.

Proponents argue that the heightened activity of HFT contributes to a reduction in trading costs in the form of narrower bid-ask spreads and an increase in market liquidity, both considered positive indicators of a robust market (Hendershott & Riordan, 2013; Brogaard et al., 2018). Additionally, advocates assert that, due to an increase in informed quotes, HF traders have enhanced the price discovery process and reduced informational asymmetries.

Conversely, sceptics contend that the real-time nature of HFT, beyond the capacity of human traders and regulators to monitor, represents unfair competition, creating a two-tiered system. Moreover, detractors argue that HF traders utilize market-abusive strategies, contributing to a decrease in liquidity resilience and an increase in volatility within the equity market.

Motivated by the ongoing debate in the financial community, this study aims to contribute a nuanced understanding of the impact of HF traders on financial markets. By employing a multifaceted research methodology, including empirical analysis, theoretical frameworks, and a simulation of a trading strategy, this thesis endeavours to unravel some of these controversies, "Separating Truth and Myth in the Criticisms of High-Frequency Trading", investigating aspects such as market quality, market competition and liquidity as well as shed light on possible policies and regulation that can be implemented to a better overall market.

To complement and explore some of these inquiries, the study employs a trading strategy on a dataset spanning from January 4, 2021, to March 31, 2021, comprising 1-minute interval data of Euro Stoxx 50 Index Futures. This analysis affords an intricate perspective on the performance of institutional versus retail traders, providing a unique vantage point for the comprehensive examination of HF trading dynamics.

2 Literature Review

Given the increasing prominence of HF traders in current financial markets, it is imperative to comprehend the theoretical implications of their presence. The HFT sector experienced swift expansion following its emergence in the mid-2000s, from a small, niche strategy to the dominant form of trading. Currently, HFT accounts for approximately 50% of the trading volume in US equity markets, according to the U.S. Securities and Exchange Commission (SEC) while in European equity markets, its market share is estimated to range between 24% and 43% of trading volume, encompassing about 58% to 76% of total orders, according to the European Securities and Markets Authority (Breckenfelder 2019).

The Concept Release on Equity Market Structure by the SEC acknowledged that HFT stands out as a major market structure advancement in recent years. It further asserted that HFT constitutes a dominant element of the existing market structure, exerting influence on almost every aspect of its performance (Securities and Exchange Commission 2010).

In market microstructure literature, the exact definition of HF traders is not entirely clear, nonetheless, they are often described as automated computer systems that rapidly solve algorithms and execute trades based on the outcomes of said algorithms. The SEC Concept Release outlined five characteristics often associated with HFT: First, HF traders execute trade orders using high-speed and sophisticated algorithms for order generation, routing and execution. Second, they employ co-location solutions and data feeds from exchanges to reduce network latency. Third, they adopt very short timeframes for establishing and liquidating positions. Fourth, they submit multiple orders that are frequently cancelled shortly after submission. Finally, they aim to conclude the trading day with a position as close to flat as possible, avoiding significant, unhedged overnight positions. However, the Concept Release did not assert that the presence of all these characteristics is mandatory for a proprietary firm to be accurately classified as HFT. Such a rigid approach might unduly restrict the classification of firms as HFT and hinder a more inclusive categorization (Securities and Exchange Commission 2014). In reality, most market participants classify HF traders as those who focus primarily on speed, with all other attributes acting as supplementary.

The absence of a precise definition has not hindered a broad consensus among market participants and academics regarding the primary strategies employed by HF traders. These strategies encompass Auto Market Making (AMM), quantitative and statistical arbitrage, directional strategies, and liquidity detection (Papalexiou 2020).

Auto Market Making (AMM) strategies serve as a modernized alternative to traditional market makers, differentiating themselves by leveraging computer algorithms to incorporate as much information to establish quotes and execute trades. Diverging from the obligations of traditional market makers, AMM HF traders operate as informal market makers, adjusting their positions based on valuation models. The integration of extensive information into quotes aims to mitigate the adverse selection problem, with most HF AMM traders opting to conclude positions by the close of the trading day.

Quantitative and statistical arbitrage strategies involve the execution of trades based on mispricing across various markets or assets. In the realm of statistical arbitrage, the focus is on trading identical or similar securities across various markets. Meanwhile, quantitative strategies center around the relative performance of securities, employing statistical models for decision-making.

Directional strategies focus on trading based on factors such as news, momentum, or order flow. HF traders employing directional strategies continuously monitor public news sources for potential trade-relevant information or observe market order flows, posing challenges for institutional traders executing large trades.

Liquidity detection strategies, the most controversial among HF strategies, encompass practices like quote stuffing, spoofing, and pinging. Quote stuffing involves rapidly entering and withdrawing multiple orders simultaneously to create confusion in the market. Spoofing involves creating an illusion of demand or supply to influence the price of the underlying security before withdrawing orders. Pinging is a strategy wherein HF traders dispatch numerous small orders to infer the presence of a substantial volume trader, subsequently adjusting the order book to capitalize on price movements away from the larger investor.

Although traditional market microstructure models propose that the inclusion of HF traders would be advantageous for financial markets, the financial community is divided regarding the benefits of HF traders. In general, empirical findings corroborate the forecasts derived from the model developed by Glosten and Milgrom (1985) as the majority of research indicates an enhancement in market efficiency and liquidity. Hendershott and Riordan (2013), Brogaard, Hendershott, and Riordan (2014), Malinova, Park, and Riordan (2018), among others, demonstrated that HF traders enhance market liquidity on average. Moreover, Sornette and Von der Becke (2011), Riordan et al. (2012) and Carrion (2013) all indicate that HF traders increase market efficiency. According to this analysis, the incorporation of HF traders into the marketplace appears to have a positive impact on market efficiency and liquidity, which is coherent with classical models' findings.

Furthermore, by substituting the traditional market maker with the HF trader, the latter can promptly furnish updated quotes incorporating both market-wide and newly available public information. This implies that the HF trader is exposed to a reduced adverse selection risk compared to the conventional market maker, given that their quotes integrate more information and are updated more frequently to mirror any recent market developments. Consequently, the likelihood of the HF trader encountering information asymmetry, where other market participants possess superior information, is diminished. Building from this association, a few conclusions can be inferred from the Glosten and Milgrom (1985) model. Initially, a decrease in the bid-ask spread is anticipated owing to the reduced adverse selection cost. Secondly, quotes are anticipated to be updated more frequently, without necessarily increasing the number of trades. However, the tighter bid-ask spread raises the likelihood of increased trading, as traders engage more in response to the reduced cost. Lastly, as informed quotes surge, it is anticipated that a larger segment of the price discovery process will be impacted by updates in quotes.

Nevertheless, market practitioners and empirical research also emphasise the adverse characteristics of HF traders and their impact on systemic risk and exploitative strategies that contribute to their unfavourable public perception (Papalexiou 2020).

Due to their near-immediate processing and response to new information, HF traders are able to cancel and submit a large number of quotes in a brief period of time. This conduct is a primary subject of criticism directed towards HF traders, as indicated by several authors who contend that it negatively impacts the integrity of the market (Hasbrouck and Saar 2007;Van Ness, Van Ness, and Watson 2014). The effectiveness of liquidity enhancement credited to HF traders comes under scrutiny amid concerns that they may retract their liquidity during periods of market turmoil, thereby casting doubt on the robustness of the liquidity they ostensibly provide.

2.1 Impacts of HFT on Liquidity

Recognizing the influence of HF traders on liquidity is crucial, given that liquidity serves as the bedrock of financial markets. While defining liquidity precisely proves challenging (Hara 1997) a widely accepted definition by Kyle (1985) encompasses three key attributes: Tightness, gauged by the cost associated with rapidly buying and selling an asset, often indicated by the spread. Depth, determined by the volume of orders present in the order book at each price level. Lastly, resiliency, assessed by the velocity at which liquidity reverts to normal following an unpredicted order shock. The initial two aspects of liquidity have received extensive scrutiny in market microstructure literature. In contrast, there has been limited exploration of liquidity resilience, particularly in understanding how HF traders influence it. This research gap is noteworthy, especially considering the irony that a primary concern about HF traders revolves around the perceived deficiency in liquidity resilience during periods of market stress.

On one hand, HF traders are perceived as exceptionally swift traders, envisioned to boost liquidity provision, reduce generation of information and transaction costs, thereby improving market efficiency. Conversely, the ultra-fast reaction capabilities of HF traders to fresh data and their capacity to foresee order flow may potentially displace liquidity. Therefore, empirical evidence regarding this matter lacks a definitive conclusion.

While a substantial body of prior research emphasizes the positive influence of HFT on liquidity, such as its role in reducing informational asymmetries (Brogaard 2010; Hasbrouck and Saar 2013; Jarnecic and Snape 2014; Jain, Jain, and McInish 2016; Li, Cooper, and Van Vliet 2018; Baldauf and Mollner 2020; Ben Ammar, Hellara, and Ghadhab 2020) a considerable number of studies concentrate on the potential adverse effects of HFT on liquidity. These effects are often attributed to heightened competition among HF traders or their extensive quoting activities (Kirilenko et al. 2017; Malceniece, Malcenieks, and Putniņš 2019; Breckenfelder 2019; Ekinci, Akyildirim, and Corbet 2019).

Brogaard (2010) investigates the involvement of 26 HFT firms, representing 68.5% of the dollar volume traded in the U.S. equity market. The findings reveal that while certain HF traders supply liquidity and others demand it at times, they primarily offer the best bid/ask quotes, enhancing overall liquidity. The study evaluates the impact of HF traders on liquidity at a daily level, demonstrating that these traders slightly reduce liquidity supply and increase liquidity demand as volatility rises. Hasbrouck and Saar (2013) explore the impact of low-latency trading activity on the market in both normal and uncertain conditions. They discover evidence of reduced quoted spreads, concluding that HFT enhances market liquidity in both scenarios. Jarnecic and

Snape (2014) validate earlier findings regarding the positive impact of HFT on liquidity while highlighting challenges faced by non-HF traders. They suggest that HF traders contribute liquidity by placing orders at various prices, either at or within the quote. Jain, Jain, and McInish (2016) utilize both traditional and newer liquidity metrics, demonstrating that reduced latency enhances market liquidity, particularly following the introduction of the Japanese low-latency trading platform, Arrowhead. Li, Cooper, and Van Vliet (2018) provide evidence that HFT enhances liquidity by increasing the number of low-frequency orders and the frequency of trades. Baldauf and Mollner (2020) propose a model that considers multiple trading venues, costly information acquisition, and various types of traders, showing that HFT boosts liquidity by reducing informational asymmetries but at the expense of price efficiency. Ben Ammar, Hellara, and Ghadhab (2020) offer evidence of HF traders positive impact on intraday liquidity, measuring it through the effective spread and decomposing it into transitory and adverse selection components. They demonstrate that the beneficial influence of HFT on liquidity results from reduced adverse selection costs. In contrast, Ekinci, Akyildirim, and Corbet (2019) reveal that HFT diminishes market liquidity in a 2015-2017 sample of 30 blue chips from Borsa Istanbul. This finding is significant given the relatively low overall HFT share (approximately 3.2% of order count and 2% of order volume) during the studied period, despite the recent introduction of colocation services and technological advancements.

In Breckenfelder's (2019) investigation within the context of HFT, an examination is undertaken to elucidate a specific pathway through which HF traders might contribute to the reduction of market liquidity, specifically by intensifying competition. The findings reveal that heightened competition among HF traders correlates with a decline in market liquidity. This study aligns with the broader research landscape, as evidenced by other scholarly works, including those by Bernales (2019) and Brogaard, Garriott, and Pomeranets (2018) which also delve into the role of HFT competition in shaping market liquidity dynamics. The latter specifically focuses on the

Canadian stock exchange Alpha, which was recently introduced. Their dataset spans four years and commences with a period devoid of HF traders, later incorporating the entry of 11. The authors provide three strands of evidence indicating that competition among HF traders results in an improvement in liquidity metrics. On the contrary, Bernales (2019) offers insights into the nuanced relationship between HFT competition and market liquidity. The study suggests that the impact of additional HFT competition on liquidity is contingent upon the existing number of HFT firms in the market. Specifically, when there are several (or few) HFT firms present, the study indicates that additional competition among HF traders can either ameliorate or damage market liquidity.

HFT encompasses various strategies, as previously discussed. However, at its core, these strategies can be classified into two main categories: market making and market taking (opportunistic). Menkveld (2013) investigated HF traders' behaviour on Chi-X and Euronext exchanges from January 1, 2007, to June 17, 2008, revealing that HF traders predominantly engaged in passive market making strategies in both markets. Similar findings were reported by Hagströmer and Norden (2013) using data from the NASDAQ-OMX in Sweden, where HF market makers represented a substantial portion of trading volume and limit order traffic compared to opportunistic HF trading strategies.

Benos and Sagade (2012) explored the informativeness of HF market makers and takers, determining that HF market takers normally possess more information. Van Kervel (2014) scrutinized order flow between slow and fast traders, discovering a positive correlation between the trading profit of HF market makers and the likelihood of trade execution. This observation is attributed to HF market makers strategically placing multiple similar limit orders to enhance the probability of execution, facilitated by their ability to swiftly place and cancel orders.

Despite their efficacy, a critique of HF market makers arises from their lack of obligation to provide liquidity, as noted by Kirilenko and Lo (2013). Barrales (2012) suggested that this absence of a liquidity provision requirement might expose equity markets to price collapses if liquidity is suddenly withdrawn. Studies by Brogaard, Hendershott, and Riordan (2014) and Anand and Venkataraman (2016) observed increased participation of HF market makers and traders on days with above-average volatility. However, the efficacy of the liquidity improvement attributed to HF traders is called into doubt due to assertions that they tend to withdraw their liquidity during periods of extreme market volatility. Extensive research has been conducted on this theory, and its confirmation by past and ongoing studies raised concerns (Easley, López de Prado, and O'Hara 2010; Anand and Venkataraman 2016).

Theoretical frameworks connect liquidity crashes to the risk-bearing capabilities of intermediaries. In the work of Huang and Wang (2008, 2010) an equilibrium model is crafted, wherein market crashes arise organically when an abrupt surge in sell orders surpasses the inadequate risk-bearing capacity of market makers. Additionally, Ait-Sahalia and Saglam (2017) establish a connection between heightened price volatility and more stringent inventory constraints for HF intermediaries, indicating their ability to bear the risk associated with increased volatility. Kirilenko et al. (2017) investigated the flash crash that occurred on May 6, 2010, marked by significant and temporary selling pressure. Throughout the four days analyzed in their study, HF traders consistently held inventories of approximately 4,000 contracts or less, a size considerably smaller than the 75,000 contracts order documented in a CFTC-SEC (2010). On the same note, market makers did not surpass net inventories of 1,500 contracts in any direction. These findings support the theory of the limited risk-bearing capacity of intermediaries during a liquidity crunch, as intraday intermediaries did not assume greater inventories when compared to pre-May 6 levels. Ait-Sahalia & Saglam (2017) delved into the behaviour of HF market makers, finding that, with increased speed, they offered greater liquidity but retracted it during periods of heightened volatility.

2.2 Commonality

Due to the tendency of HF traders to employ similar strategies, it can be anticipated that this conduct will give rise to heightened commonality in terms of liquidity resilience, particularly in adverse market conditions. Liquidity commonality refers to the scenario where the liquidity of a particular security moves in tandem with the overall market, inducing synchronized changes in liquidity. This phenomenon has the potential to cause a significant rise in systematic liquidity risk, resulting in sudden shortages of liquidity.

Liquidity-demanding HF traders often employ similar strategies concurrently, leveraging correlated signals. Consequently, these traders may simultaneously withdraw liquidity, posing a risk to market functionality. Conversely, HF market makers, typically beneficial to market operations, can paradoxically become unfavourable as a result of liquidity commonality.

Anand and Venkataraman (2016) posit that HF market makers, prone to exiting the market under unfavourable conditions, may introduce vulnerabilities. Cespa and Foucault (2014) findings underscore the correlation between liquidity and price informativeness, contributing to market contagion. They specifically highlight a potential feedback loop resulting in liquidity contagion from individual securities to the broader market.

Malceniece, Malcenieks, and Putniņš (2019) support this perspective, indicating that approximately one-fifth of the increased liquidity co-movement stems from HF traders exiting the market during adverse conditions, with heightened effects during periods of high volatility. They identify correlated liquidity demand from opportunistic HF traders and increased monitoring capabilities of HF market makers as common drivers of heightened co-movement of liquidity. Additionally, their analysis reveals significant liquidity co-movement, particularly among medium and small-cap stocks, supporting the idea of HF traders' incremental monitoring capacity and a habitat effect (Ersan et al. 2021).

Anagnostidis and Fontaine (2020) additionally illustrate that, owing to the swift dissemination of information and the adoption of shared trading strategies, HF traders exhibit higher liquidity supply co-variation compared to normal traders. They highlight the dynamic nature of liquidity commonality, emphasizing heightened systematic risk in securities extensively traded by HF traders during periods of market-wide distress.

2.3 Competition and Fairness

HFT has generated substantial debate in financial circles, particularly regarding its perceived influence on market fairness and the establishment of a two-tiered marketplace. This stems from the fact that HF traders require low latency access, providing them with a speed advantage over other traders. This preferred access advantage is not a novel concept and predates the emergence of HFT. Hasbrouck and Saar (2013) acknowledge that co-located traders enjoy a significant timing advantage, similar to how floor traders had a timing edge over off-floor traders.

In 2009, Andrew Brooks, the head of US equity trading for T Rowe Price, remarked, "But we're moving toward a two-tiered marketplace of the high-frequency arbitrage guys, and everyone else. People want to know they have a legitimate shot at getting a fair deal. Otherwise, the markets lose their integrity." (Narang 2013, p. 280). The argument posits that superfast computers, algorithms, and telecommunication setups, being expensive and beyond the reach of the average person, contribute to a two-tiered system favouring HF traders. However, a fundamental flaw exists in this perspective. It suggests that individuals who are more knowledgeable and invest in costly infrastructure to enhance their competitive edge possess an unfair advantage. Doesn't Warren Buffett possess an unfair advantage over others by arriving at the table with a good idea sooner than you? Whether attributed to superior information access or more effective information processing by analysts, the question of whether this confers an unfair advantage arises. Similarly, in the realm of sports, Real Madrid, with the financial capacity to recruit top talent by offering substantial salaries, could be considered as having an advantage in assembling a more skilled team than their counterparts. The fairness of this advantage comes into question, especially when substantial payroll investments do not culminate in winning the Champions League or La Liga. The capitalist principle posits that individuals willing to take risks are entitled to potential rewards, emphasizing the unfairness of preventing some from seizing opportunities. While acknowledging legitimate concerns about certain HFT practices, such as flash trading, quote stuffing and naked sponsored access, categorizing the entire activity as inherently unfair is deemed inaccurate. Three key arguments are presented to counter this perception:

1. Investment in expensive infrastructure doesn't guarantee success. Many HF traders have invested millions in infrastructure, only to end up with significant financial losses. Success in HFT requires a high level of intelligence to outsmart competitors armed with fast technology or in-depth analytical capabilities.
2. The markets have become more egalitarian than they have ever been. While historical advantages existed for firms in proximity to physical exchanges or with early access to telephones, the gap has narrowed considerably. Today, the advantage of the fastest HFT firms over the average online brokerage customer is on the order of a fraction of a second, compared to the advantage of a firm that had staff on the exchange floor, trading in real-time, where end investors relied on end-of-day prices in the next morning's newspaper (Narang 2013).
3. Investments in infrastructure, technology, skilled personnel, and other competitive advantages are inherently risky. If successful outcomes are achieved, they should not be retroactively considered unfair. Anyone can pursue the training and risk capital required for advantages in HFT, and if barriers exist, it reflects a more profound issue in our society. However, it's important to note that HFT should not be criticized for this problem.

In conclusion, the argument that HFT is inherently unfair or creates a two-tiered marketplace lacks merit. While HF traders possess speed advantages, similar advantages exist for individuals with above-average intelligence or those investing time and money in a thorough analysis of investment decisions.

3. Data and Model Methodology

In the pursuit of understanding the influence and performance of HFT, an agent-based model framework was introduced to comprehensively test and simulate the dynamics under three different scenarios. The model employed evaluates the impact of a HFT strategy, including a backtested approach to assess profitability for retail and institutional investors. This section explains the chosen methodological approach of backtesting a HFT strategy based on an equity index future and is divided into four subchapters. The first section describes the data set and some pre-defined rules. The second section presents the underlying index future strategy without considering transaction costs and only using the trade price as well as the portfolio performance. The third section covers the same strategy but contemplates implicit transaction costs aggregating the OHLC (Open High Low Close) data variables for both the bid/ask price.
The fourth section covers the same strategy but contemplates explicit fixed transaction costs, using 2 different transaction fees (Fees Pro and Fees Retail), and therefore 2 different profits and losses (PNL Pro and PNL Retail).

3.1 Data Set and Trading Rules

The foundation of the backtesting procedure lies in the Euro Stoxx 50 Index Futures EUR (Ticker: VG1 Index), sourced from Refinitiv Eikon. The dataset utilized spans from January 4, 2021, to March 31, 2021, providing 1-minute interval data. This dataset intricately captures essential information, including the date, hour, specific minute within the hour, trading price, bid/ask price. Based on this data, it was calculated the average price for each minute (using the last 20 periods), a standard deviation for each recorded t, (using the last 20 periods) and volatility.

3.2 Strategy 1 – Not considering Transaction Costs and using the Trade Price

The HFT strategy generates signals based on the relationship between the trade price and the moving average, adjusted by a volatility factor. A negative signal (-1) is produced if the trade price exceeds the upper threshold, while a positive signal (1) is generated if the trade price falls below the lower threshold. Otherwise, the signal remains neutral (0).

The sell signal is determined by the formula:

$$P_t > \frac{\sum_{i-21}^{i-1} P}{20} + \sigma \times \sqrt{\frac{\sum \left(P_i - \frac{\sum_{i-21}^{i-1} P}{20} \right)}{20}}$$

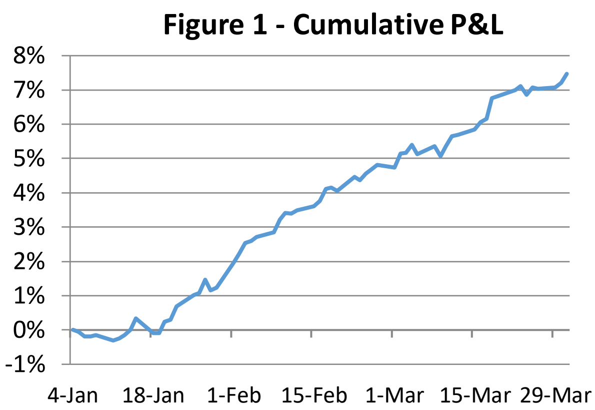
The buy signal is determined by the formula:

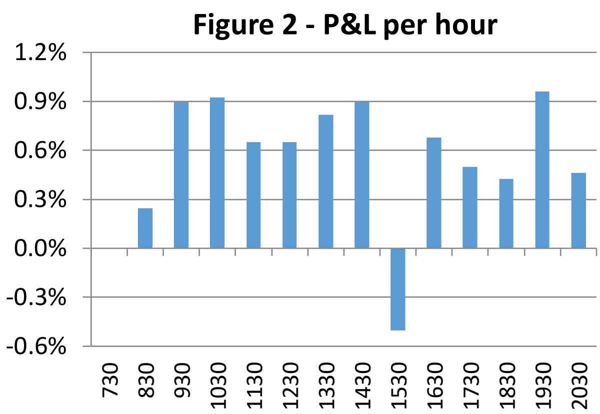
$$P_t < \frac{\sum_{i-21}^{i-1} P}{20} + \sigma \times \sqrt{\frac{\sum \left(P_i - \frac{\sum_{i-21}^{i-1} P}{20} \right)}{20}}$$

Where σ is the number of standard deviations, P_t is the price at moment t, i is a period (a minute). Signals are generated every second and are processed every time the Stoxx 50 futures index opens (7h to 21h, in the Refinitiv Eikon data). In the sample from and therefore are executed in the subsequent period t+1 (time-lag). The three strategies are using price-based simple moving averages (SMA) with equally weighted prices of 20 periods (20 minutes). Moreover, 260 trading days per year are used to annualize return, volatility, and other metrics.

Performance:

The trading strategy, presented below in Figure 1 with the cumulative Profit and Loss (P&L) and in Figure 2 with the P&L per Hour, has shown robust performance with an annualized return of 32%, low volatility (standard deviation of 3%), and an impressive Info Sharpe Ratio of 9.42, indicating substantial excess return relative to risk. Moreover, positive returns were generated on 78% of days, emphasizing consistent performance. While these metrics suggest a well-performing strategy, it's essential to acknowledge that not accounting for transaction costs and assuming universal trade price executability is unrealistic.





Assumptions:

The current trading strategy assumes universal trade price executability, overlooking real-world factors like market liquidity and bid-ask spreads. It relies on market orders without considering order book intricacies, potentially benefiting from incorporating diverse order types. Stability across different times and responsiveness to time-dependent patterns are vital for adaptability. Implicit and explicit transaction costs, including bid-ask spreads, are not considered, which is crucial for a realistic trading representation.

Model Contributions and Implications:

The model contributes to understanding HFT strategy dynamics, but questions arise regarding the impact of transaction costs and the assumption of universal trade price executability. The results may have implications for HFT strategy optimization, suggesting the need for further analysis on transaction cost sensitivity and trade price assumptions.

3.3 Strategy 2 – Considering Implicit Transaction Costs

The second strategy introduces realism by incorporating implicit transaction costs, considering Bid/Ask and Open, High, Low, Close (OHLC) data within the same trading framework. However, this realism comes at a cost, as demonstrated by the strategy's performance:

The sell signal is given by:

$$P_t^{ASK} > \frac{\sum_{i-21}^{i-1} P}{20} + \sigma \times \sqrt{\frac{\sum \left(P_i - \frac{\sum_{i-21}^{i-1} P}{20}\right)}{20}}$$

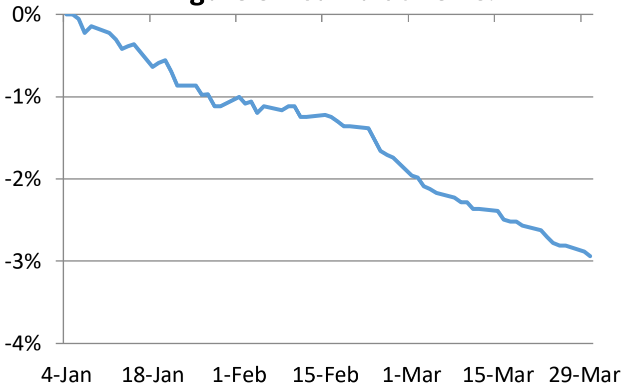
The buy signal is given by:

$$P_t^{BID} < \frac{\sum_{i-21}^{i-1} P}{20} - \sigma \times \sqrt{\frac{\sum \left(P_i - \frac{\sum_{i-21}^{i-1} P}{20}\right)}{20}}$$

Performance:

The second strategy, presented below in Figure 3 with the cumulative Profit and Loss (P&L), shows a challenging scenario with an annualized return of -12%, indicating an overall loss. The standard deviation of 1%, pointing to relatively stable returns. An Info Sharpe Ratio of -10.47, reveals that the strategy's returns did not sufficiently compensate for the associated risk, signalling suboptimal risk-adjusted performance. Positive days accounted for approximately 20.97%, denoting a limited frequency of profitable days.

Figure 3 - Cumulative P&L



Model Contributions:

The model adds realism by accounting for implicit transaction costs, incorporating OHLC data which enhances insights into price movements during different market phases, but questions emerge regarding the strategy's viability and effectiveness in a real-world scenario. Certainly, the use of 1-minute intervals is not ideal and the model is probably missing rapid market movements, suggesting potential benefits from finer time granularities.

Possible Implications:

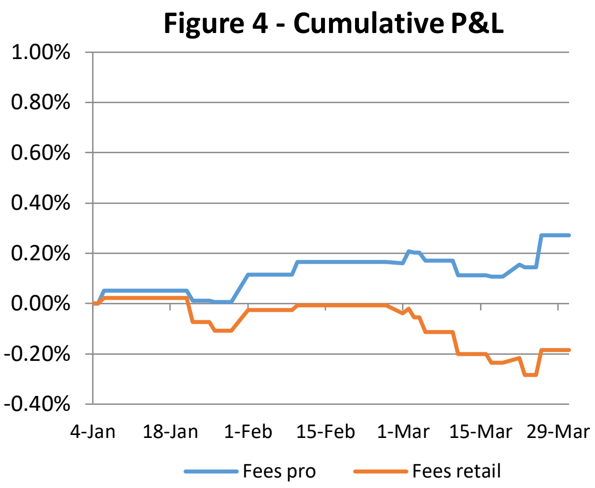
The findings underscore the importance of factoring in transaction costs for a more accurate assessment of strategy performance. Strategies that perform well in a cost-free environment may face challenges when transaction costs are considered, emphasizing the need for careful consideration and optimization.

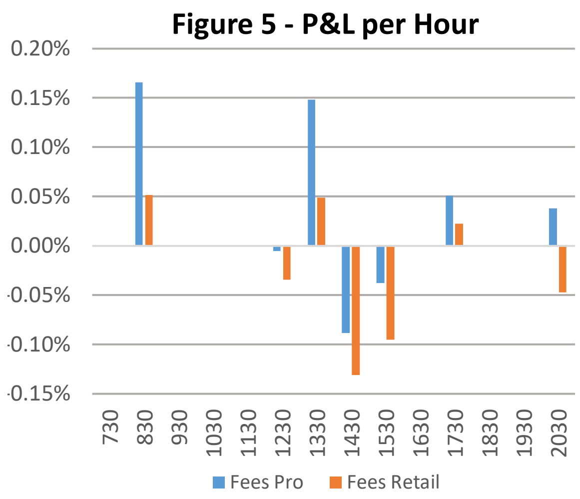
3.4 Strategy 3 – Considering Explicit Transaction Costs

In this strategy, the same trading framework is utilized, but explicit transaction costs are considered, distinguishing between Professional and Retail fee structures. The transaction costs are set at 0.3 basis points (bps) per trade for Professional HF traders and 1.7 bps for Retail HF traders, primarily representing the bid-ask spread when buying and selling assets. The analysis of this strategy yields distinct outcomes:

Performance:

For Professional Fees, the strategy produced a positive annualized return of 1.12%, reflecting profitability. The standard deviation of 0.42% suggests moderate volatility in returns, maintaining stability. An Information Ratio of 2.65 indicates a notably positive excess return relative to risk, portraying a favourable risk-adjusted performance. Approximately 10% of days resulted in positive returns, demonstrating a modest frequency of profitable days. Contrastingly, under Retail Fees, the strategy exhibited a negative average return of -0.77%, signalling an overall loss. The standard deviation of 0.45% reflects moderate volatility in returns for Retail fees. An Information Sharpe Ratio of -1.73 indicates that the strategy's returns did not effectively compensate for risk, suggesting a less favourable risk-adjusted performance. Similar to Professional Fees, approximately 10% of days resulted in positive returns and both strategies have executed 32 trades. The strategies' performance is presented below in Figures 4 and 5 with the respective cumulative Profit and Loss (P&L) and P&L per hour.





Model Contributions:

The model highlights the nuanced performance characteristics between Professional and Retail fee structures, raising questions about the adaptability and effectiveness of the strategy under different cost scenarios. This is demonstrated by the drastic performance difference between the professional and the retailer by applying different explicit transaction costs.

Possible Implications:

The findings emphasize the need for practitioners to carefully consider and choose transaction cost structures based on their trading objectives. The strategy's performance varies significantly under different fee structures, underlining the importance of aligning costs with the specific nature of HFT activities.

Limitations:

The third strategy bears notable limitations. It is responsive to predetermined transaction costs, which may not properly mirror actual circumstances. There are exchanges and brokers with complex fee pricing structures, featuring different fee rebates depending on whether the transaction is a maker or taker, whether it provides or takes liquidity, to incentivize traders to provide liquidity. The method of generating signals, which relies on a simple formula, has the potential to oversimplify the complexities of market dynamics. The backtesting period is constrained, offering solely a snapshot of certain market circumstances. Although the strategy demonstrates positive results, its reliability is uncertain. The presumed equal-weight allocation to both buy and sell signals may overly simplify the process of decision-making. It is important to consider these restrictions when analysing and implementing the strategy, emphasising the importance of being careful and the necessity for additional improvement.

4. Conclusions

In conclusion, the relationship between the model's insights and the research findings highlights the importance of holistic approaches to market structures, regulatory frameworks, and technological advancements to ensure fair and efficient financial landscapes, catering to the diverse needs of all market participants.

4.1 Model Conclusions

The existing Liquidity Provision Rebates follow a tiered structure favouring the most active participants for better rebate tiers. Although rebates incentivize liquidity provision, the tiered system creates obstacles for lower-volume participants aiming for profitable passive order posting. Transitioning to a flatter or entirely flat rebate structure would mitigate this challenge. Moreover, regulators should equip themselves with technology for effective market monitoring and enforcement. This understanding is becoming increasingly recognized, with the SEC taking notable steps in the right direction.

The model can associate investment, efficiency, and the size of the company with potentially higher profitability due to lower commissions (liquidity rebates) resulting from higher trading volumes, expertise in refining the model, and the ability of top companies to recruit the best professionals in the field, thereby achieving more significant expected returns.

In conclusion, the results of the last strategy performance test underscore a significant challenge for retail investors engaging in HFT. Despite the presence of relatively modest explicit trading costs, the findings reveal that these costs are ultimately unsustainable for retail investors. This observation suggests that the intricacies and rapid pace of HFT may be better suited for institutional investors or specialized trading entities with the resources and infrastructure to manage such costs effectively. As HFT continues to reshape the landscape of financial markets, it becomes increasingly apparent that retail investors may face considerable barriers in participating in this domain due to the prohibitive nature of associated trading costs. This insight prompts a deeper examination of the broader implications for retail investors navigating the evolving dynamics of contemporary financial markets.

4.2 Research Conclusions

The findings from my study contribute to the ongoing discourse regarding the advantages and drawbacks associated with HFT activity. Advocates of HFT argue that it enhances price discovery by rapidly reflecting market news and providing liquidity. Supporters also argue that the increased involvement of HFT leads to lower trading costs through narrower bid-ask spreads and improved market liquidity, considered positive signals of a robust market (Hendershott & Riordan, 2013; Brogaard et al., 2018). They also assert that HFT, by generating more informed quotes, enhances the price discovery process and mitigates informational imbalances by rapidly reflecting market news. All of these statements were confirmed by the majority of the empirical research and can be derived from the Glosten and Milgrom (1985) classical model.

On the other hand, critics claim that HFT results in unfair competition and establishes a two-tiered system. The findings from my study posit that this argument lacks merit. While HF traders possess speed advantages, similar advantages exist for individuals with above-average intelligence. Success in HFT requires in-depth analytical skills and a significant cost in infrastructure to outsmart competitors. If successful outcomes are achieved, they should not be retroactively considered unfair. Anyone can pursue the training and risk capital required for advantages in HFT, and if barriers exist, it reflects a more profound issue in our society. However, it's important to note that HFT should not be criticized for this problem.

The unfair Detractors further argue that HFT practitioners employ strategies deemed market-abusive, contributing to reduced liquidity resilience and heightened volatility in the equity market. This was confirmed by this study and the majority of research as potentially harming market functionality, during extreme market movements partially given by the increase in commonality of liquidity resilience.

4.3 Policy Implications

Rather than constituting an independent strategy, HFT leverages cutting-edge advancements in market access, data availability, and order routing to optimize returns for established trading strategies. Therefore, the assessment and regulatory discourse on HFT should shift focus toward understanding the underlying strategies, moving beyond a singular emphasis on HFT itself. HFT represents a natural progression in securities markets, evolving over time and incorporating quote machines, direct market access tools, and smart order routing systems. This evolution, spurred by competition, innovation, and regulation, mirrors the development trajectory of other technologies. HFT allows sophisticated market participants, particularly in the technology sector, to legitimately reap rewards and compensation for market, counterparty, and operational risk exposures.

Given the substantial market impact of HFT, effective oversight, transparency, and open communication are critical for fostering confidence and trust in securities markets. With HF traders commanding more than one-third of trading volume in major markets, regulators must scrutinize the resilience and dependability of HFT systems and risk management procedures. Entities engaged in HFT carry the responsibility of proactively communicating internal safeguards and risk management measures, acknowledging the constraints on publicly releasing intellectual property rights. However, a noticeable reluctance of entities to engage with the public, media, and fellow market participants can erode trust. HFT entities should actively underscore their role as an evolutionary force in modern securities markets, providing significant liquidity and contributing to price discovery for the collective benefit of all market participants.

4.4 Future Research

Exploring further avenues for research, it would be worthwhile to conduct a detailed examination of market aspects such as volatility and systemic risk. Additionally, it's crucial to assess the adaptive evolution of HF traders and improvements in their HFT algorithms over time, gauging their consequential impact on the overall market, whether positive or negative.

Regarding the model, a nuanced analysis based on diverse pricing structures for HF traders as makers or takers presents an intriguing avenue. It would also be interesting to extend the backtesting period to evaluate the strategy's performance in diverse market conditions, including high volatility or low liquidity and incorporate additional data sources, such as market news or macroeconomic indicators, to improve the strategy's decision-making process. Furthermore, integrating inventory management into the strategy, testing diverse HF trading approaches and their impact on different equity index futures, and obtaining data at the millisecond level would offer valuable insights.

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