WEP Warwick Evans Publishing

Transactions on Economics, Business and Management Research
ISSN: 2960-1789, eISSN: 2960-2254 | Volume 14
AFTEM 2024

Algorithms and High-Frequency Trading in Financial Markets

Zhuoma Danzeng [1], Hao Gao [2,*] and Ziqi Guan [3]

[1] School of Business, Dublin City University, Dublin, Ireland

[2] School of Data Science, Chinese University of Hong Kong (Shenzhen), Shenzhen, China

[3] College of Physical Science and Technology, Lanzhou University, Lanzhou, China

* Corresponding Author Email: 122040051@link.cuhk.edu.cn

Abstract. This paper examines the transformative impact of high-frequency trading (HFT) and algorithmic trading (AT) on financial markets. With the development of computer technology and the globalization of financial markets, HFT and AT have become the main trading methods in financial markets. The application of these technologies has not only changed the way trades are executed but has also significantly impacted market structure and participant behavior. FT utilizes ultra-fast algorithms and network technology to execute trades at high speeds and capture small price differences.AT automatically executes trades based on pre-determined strategies, which improves efficiency and reduces human error. Both approaches increase market liquidity and speed, raising challenges such as market manipulation and systemic risk. This study examines these trading mechanisms' strategies, technological underpinnings, and market effects, emphasizing the need for strong regulatory frameworks to ensure fair and stable markets. The study also discusses the role of data visualization in analyzing trading activities and its limitations, highlighting the potential of advanced visualization techniques to improve market analysis.

Keywords: High-frequency trading; Algorithmic trading; Data visualization.

1. Introduction

With the rapid advancement of technology, the trading methods in financial markets have undergone profound changes. High-Frequency Trading (HFT) and Algorithmic Trading (AT), as significant components of modern financial markets, have greatly altered the speed and efficiency of trading. HFT utilizes advanced computer algorithms and high-speed network connections to execute a large number of trades in extremely short periods, aiming to capture minute price differences in the market. Algorithmic trading, on the other hand, automates the execution of trading instructions based on pre-written strategies, thereby reducing human decision-making errors and delays. The above both has a great impact on financial markets.

Recent studies have shown the impact of high-frequency trading and algorithmic trading on financial markets. HFT can have a positive effect on the market. Budish E., et al., in 2020 showed that HFT can improve market quality by narrowing bid-ask spreads and providing liquidity [1]. However, there are also risks associated with HFT. Menkveld A J in 2022 pointed out that HFT may lead to increased market volatility and flash crashes [2]. Similarly, algorithmic trading also plays an important role in the market. Mizrach B. and Neely C J in their 2021 paper, argue that algorithmic trading has demonstrated excellence in enhancing execution efficiency and reducing transaction costs [3].

While these trading methods have enhanced market liquidity and efficiency, they have also introduced new challenges such as market manipulation and systemic risk. This paper reviews the development, technical implementation, application scenarios, and impacts of HFT and AT on financial markets, aiming to provide a reference for further research and practice. This paper will introduce algorithmic trading and high-frequency trading in the second section, including the overview and strategies of algorithmic trading and high-frequency trading, as well as the impact analysis on the market after the role of algorithmic trading and high-frequency trading. Then, in the third section, this paper will show the application of data visualization in the research, including the

Content from this work may be used under the terms of CC BY-NC 4.0 licence (https://creativecommons.org/licenses/by-nc/4.0/).
Published by Warwick Evans Publishing.

application of time series diagram, scatter diagram and heat map, and put forward the limitations and improvement methods of data visualization at the end of the third section. Finally, the paper will be concluded in the fourth section, putting forward views on high-frequency trading and algorithmic trading, suggestions for market regulators and participants, and ideas for future research.

2. Algorithmic Trading and High-frequency trading

2.1. Overview of Algorithmic and High-Frequency Trading

Algorithmic trading and high-frequency trading are two important forms of programmed trading in modern financial markets, which find and exploit trading opportunities through automated trading strategies. This section will briefly explain the definitions and characteristics of both and compare some of the differences and roles between them.

2.1.1. Definition and evolution of algorithmic trading

Algorithmic trading is any trading that uses complex algorithms to automate the trading process [4]. Algorithmic trading is a kind of programmed trading method, which determines the timing, price, and quantity of trading orders through computer programs and mathematical models to reduce market impact costs and improve trading efficiency and trading concealment. It utilizes large single split, hidden trading, and other means to seek the best trade execution path, effectively reducing transaction costs, so it is widely used in the stock, futures, foreign exchange, options and bond markets, and so on [5].

This type of trading is different from traditional trading. Traditional trading is based on practitioners ’experience, market analysis, and so on, and therefore has a relatively high probability of error and is subjective. Algorithmic trading has roots tracing back to the 1970s when the financial industry started adopting computer technology for trading purposes [6]. And then in the 1980s, academics began to conduct theoretical research on algorithmic trading. At the same time, regulators introduced a series of regulatory policies and trading rules, which changed the microstructure of the market to a certain extent. Then in the 1990s, electronic trading appeared in the market, which made a huge change in the scene. There has also been a gradual shift in the way people trade from on-market to electronic online platforms and this signals that algorithmic trading has begun to build the foundations of its magnificent castle. Algorithmic trading has been heavily utilized since the beginning of the 21st century, and due to technological advances, more efficient and advanced algorithms are gradually becoming available on the market for people to use. Algorithmic trading strategies evolved from simple execution algorithms to complex models that analyze market data, identify patterns, and execute trades based on predefined rules [6]. The emergence of such transactions has also led to the introduction of new policies and regulations by local regulators to control and stabilize the market.

2.1.2. Characteristics and technical basis of high-frequency trading

High-frequency trading (HFT) typically refers to trading activity that employs extremely fast automated programs for creating, routing, canceling, modifying, and executing orders in electronic markets [7]. Its operation relies on high-speed and complex computer algorithms for generating, transmitting, and executing orders. The process of rapidly establishing and liquidating trading positions is realized through direct access to the exchange's data link. The system is capable of efficiently placing and canceling large volumes of orders in a short period. It ensures that all positions are properly processed at the end of the trading day, thus demonstrating a high degree of automation and precision that meets the strict requirements of modern financial markets for efficient trading systems.

The successful execution of HFT strategies relies heavily on a robust technological infrastructure that facilitates rapid data processing, low-latency connectivity, and efficient trade execution [8]. And the underlying framework for high-frequency trading is built by hardware. This includes but is not limited to high-performance computing components and low-latency processors, among others. In addition to this, high-frequency trading requires the use of high-performance programming languages, multi-threaded parallel processing, and excellent algorithmic trading strategies to support the operation.

2.1.3. The role and difference between the two in financial markets.

Algorithmic trading executes trades using computer algorithms and mathematical models to reduce transaction and friction costs. At the same time, it increases trading efficiency and reduces the risk of human error. Algorithmic trading also helps investors achieve more accurate trade execution as it can optimize the trade execution process based on a variety of predefined strategies. And high-frequency trading through automated trading procedures, can quickly capture arbitrage opportunities and the fastest speed and optimal price transaction, thus maximizing investment returns [5].

Despite the emergence of high-frequency trading (HFT) as a prominent subset of algorithmic trading [6]. But there are still some clear differences between the two. Where high-frequency trades are executed much faster than algorithmic trades, usually at the microsecond or nanosecond level. As a result, high-frequency trades are executed very frequently, while algorithmic trades do not necessarily have high frequency. There is also a clear difference in emphasis between the two: algorithmic trading focuses on execution efficiency and cost control, while high-frequency trading focuses on utilizing the speed advantage to catch the market opportunities.

Thus, algorithmic trading and high-frequency trading play different roles in the financial markets, and each of them has unique advantages and challenges.

2.2. Strategies for algorithmic and high-frequency trading

2.2.1. Common algorithmic trading strategies

(1) Trend Following Strategy

Trend Following Strategy assumes that the price will continue along the established trend, so investors will trade when the trend is established (buy when the price continues to rise and sell when the price starts to fall). Recent research has shown that double and triple SMA strategies perform well in trend following. These strategies use different combinations of short-term and long-term SMAs to screen for trends and initiate trades through SMA crossovers [9].

(2) Mean Reversion Strategies

The Mean Reversion Strategy assumes that prices will revert to their mean and trades by detecting price deviations from the mean. This strategy capitalizes on short-term price fluctuations in the market by buying undervalued assets and selling overvalued assets.

The field of machine learning, especially few-shot learning, has significantly enhanced the effectiveness of mean-reverting strategies, allowing trading strategies to quickly adapt to new market conditions and improve performance during e.g., COVID-19 outbreaks [10].

(3) Arbitrage Strategy (Arbitrage Strategy)

Arbitrage strategies take advantage of price differences in markets to engage in risk-free arbitrage, by simultaneously buying and selling underlying assets in different markets. Modern arbitrage strategies combine advanced statistical modeling and machine learning algorithms to more effectively detect price mismatches and mean-reversion patterns, improving profitability [10]. Recent research has used advanced statistical models and machine learning algorithms, such as deep reinforcement learning and self-supervised learning, to improve the performance and adaptability of statistical arbitrage strategies. These methods are able to detect spread and mean-reversion patterns in the market more efficiently [11].

(4) Market Neutral Strategy (MNS)

A market neutral strategy offsets the overall risk of the market by simultaneously buying and selling the underlying asset, the goal of this strategy is to profit without being affected by the overall market movement [12]. Common market-neutral strategies include pair trading, Long/Short strategies, etc. With the evolving application of neural networks and advanced statistical methods, market-neutral strategies can be used to minimize market risk by balancing long and short positions while taking advantage of price differentials to profit [10].

2.2.2. Strategies and Execution Mechanisms for High Frequency Trading

(1) Strategies for High Frequency Trading

Common high-frequency trading strategies include market-making strategies, statistical arbitrage and event-driven strategies. In terms of pricing, new research has used machine learning and high-frequency data analytics to improve asset pricing models so that they can more accurately reflect market microstructure and the impact of high-frequency trading [13].

(2) Execution Mechanisms of High-Frequency Trading

The execution mechanism of high-frequency trading is usually categorized into two aspects: technical architecture and execution speed. The technical architecture requires hardware with low-latency servers and high-speed network connections, as well as software with specialized trading platforms and efficient algorithms. In high-frequency trading, the speed of execution will have a direct impact on returns, and state-of-the-art technology to minimize latency (e.g., fiber-optic communications, direct market access) is required in order not to affect the expected trades.

2.2.3. Strategy Diversity and Market Adaptability

(1) Strategy Diversity

Due to the large number of strategy options, in practice it is important to choose strategies to try out according to different market environments. Multiple strategies can be combined to diversify risk and enhance returns, or artificial intelligence and machine learning can be used to enhance strategy innovation and adaptability [12]. Recent risk management research combines machine learning algorithms, such as random forests and deep neural networks, to predict extreme risk events and tail risks in high-frequency trading [14].

(2) Market Adaptability

It is important to pay attention to the performance of the strategy under different market conditions: bull market, bear market, oscillating market, etc., which can be adjusted according to the market changes in order to maintain competitiveness [15].

2.3. Market impact analysis

2.3.1. The effect on market liquidity

Market liquidity refers to the possibility of market participants trading at market prices. It is a relationship between the time scale of the investment (the ease with which it can be converted into cash) and the price scale (the discount compared to the fair market price). Liquidity is an important factor in studying market operation. A well-functioning market basically has good liquidity, and a lack of liquidity often leads to financial crises. Methods such as realized spread, effective spread, bid-ask spread, trading volume, depth, and weighted depth are commonly used to measure liquidity. Because foreign exchange is more liquid, HFT has less impact on foreign exchange than on stocks. In the US market, there was no proof that high-frequency traders exited the market when the market was depressed. When algorithmic trading was applied to all stocks on the New York Stock Exchange, spreads narrowed, meaning that implementing algorithmic trading improved liquidity. And for large stocks, this kind of phenomenon is more obvious. After the introduction of HFT into the Belgian stock market, bid-ask spreads decreased within a year compared to those that were not traded by HFT entrants. Canada's Alpha exchange also saw an improvement in its spread metrics after the arrival of

HFT firms. Although the use of HFT can significantly improve the liquidity of stock markets in most countries, HFT has no effect on small stocks in the UK because HFT is not so active in British trading, and HFT has little effect on small stocks [16].

2.3.2. The effect on price volatility

Price volatility is a basic measure of financial stability. Sharp price fluctuations can be a factor in market instability and may affect the operation of the stock market. In 2022, research by Ben Ammar Imen and Hellara Slaheddine showed that changes in intraday high-frequency trading intensity can cause changes in intraday volatility [17]. In stable markets, like liquidity, HFT has a stronger impact on stock volatility of large stocks. As the intensity of HFT increases, the volatility of stocks decreases. However, under tight markets, HFT can lead to increased stock price volatility. HFT traders respond more quickly to market monitoring and adjustment, so in situations of high uncertainty, or in the event of an intraday slump, they avoid adverse order submission and cancel prior orders to adapt to the market. At the same time, HFTS consume more liquidity, leading to increased stock price volatility. It follows that the impact of HFT is both positive and negative in different market situations. How to properly use HFT to obtain its benefits while avoiding risks is a major issue that needs to be considered today.

2.3.3. The effect on market efficiency and fairness

One of the characteristics of HFTs is their ability to discover and exploit short-term price regularities with great speed. In order to facilitate the risk management decisions of traders and the choice of investment programs, it becomes very important to study the role of HFT on market efficiency. By studying the effect of HFT on market efficiency, people can understand the contribution of high-frequency trading in the price discovery process, so as to help traders make decisions and choices. According to Ben Ammar Imen and Hellara Slaheddine in 2020, HFT activities quickly, efficiently and accurately incorporate information into prices, and market quality indicators improve in the presence of HFT [18]. Regarding the fairness of HFT, in the discussion of James J. Angel and Douglas McCabe, it is divided into two parts: procedural fairness and distributive fairness [19]. From the point of view of procedural fairness, the HFT is fair because the exchange's data centers provide services equally to anyone at a published price. From the perspective of distributive justice, it can be regarded as whether it causes harm to others, and many HFT strategies do not cause harm to others, so HFT strategies themselves are fair. However, some traders abuse HFT to try to manipulate the price and profit from it, which causes harm to others and is unfair. Therefore, it is the user of the HFT rather than the HFT that decides whether it is fair. To ensure the fair operation of the market, it needs market supervision and everyone's joint efforts.

3. Application of data visualization in research

3.1. Application of timing diagrams in displaying trading activities

The timing diagram is used to show interactions when the primary purpose of the diagram is to reason about time; it focuses on conditions changing within and among lifelines along a linear time axis [20]. It is a chart that shows the changes in time series data, which visualizes the trend of data changes over time by connecting data points in chronological order to form a continuous line or curve.

Timing diagrams are also widely used in trading activities, including stock charts, depicting changes in trading volume, analyzing market volatility, displaying trading signals generated in high-frequency trading, and so on.

A typical example of a time series chart application is showing the change in stock prices over time. As shown in Fig. 1, it uses the matplotlib library in Python to plot a time series graph of a stock's closing price over time:

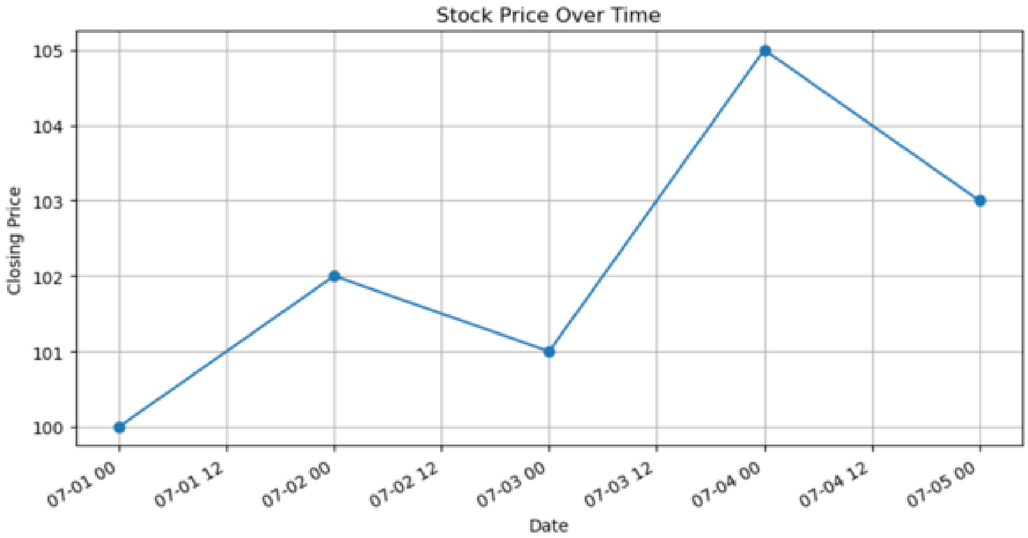

Fig 1. Timing diagram generated with the above Python code.

By way of example, timing diagrams are widely used in demonstrating trading activity, they provide traders with a quick and intuitive way to understand and analyze market changes.

3.2. Application of scatterplot in analyzing price changes

The Fig. 2 below shows the closing stock price of Apple Inc. from February to July 2024 clearly using a scatter plot. As can be seen from the graph, the stock price dropped from 190 to at least 170 (the lowest value) from February to the end of April; the stock price rose continuously thereafter until July when it reached the top of the range of values taken, 220.

The chart below presents the five-month stock price picture in a more visual way. Due to the nature of the data, the daily stock prices are put together in a scatter plot to show not only the corresponding trend, but also some values that deviate from the overall trend. algorithmic trading is any trading that uses complex algorithms to automate the trading process.

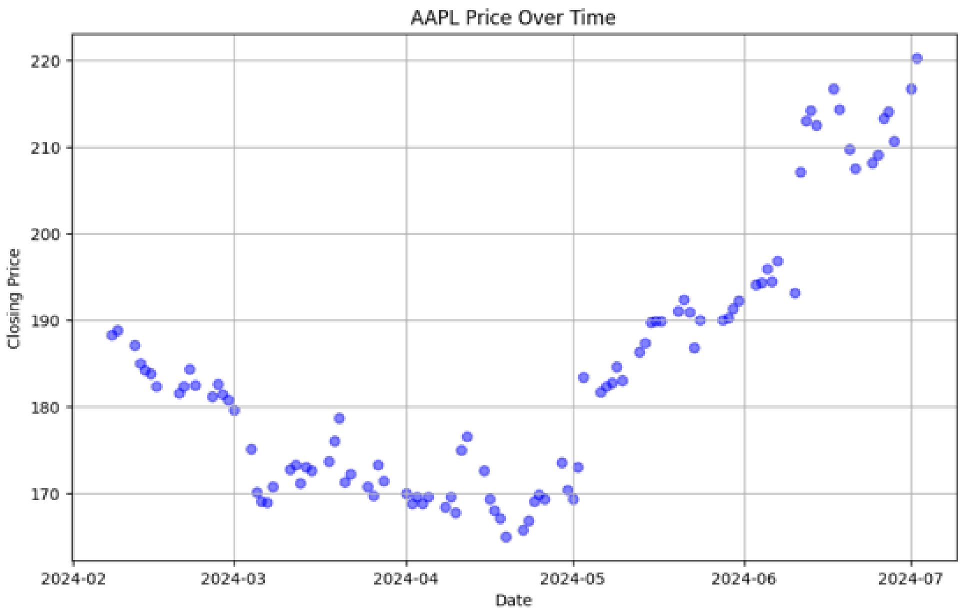

Fig 2. The closing stock price of Apple.

3.3. Application of heat map in trading volume distribution

Heat map is a very intuitive data visualization tool, which shows the distribution density or intensity of data in different areas through color change. Using heat map in market trading volume can facilitate traders to analyze data and make strategies. In the time dimension, the thermal map can be used to observe which periods have high trading volume, thus helping traders grasp the trading rules of the market. In terms of price, the heat map can intuitively and quickly show the volume density corresponding to different price ranges, so as to understand the market's transaction willingness at different price levels.

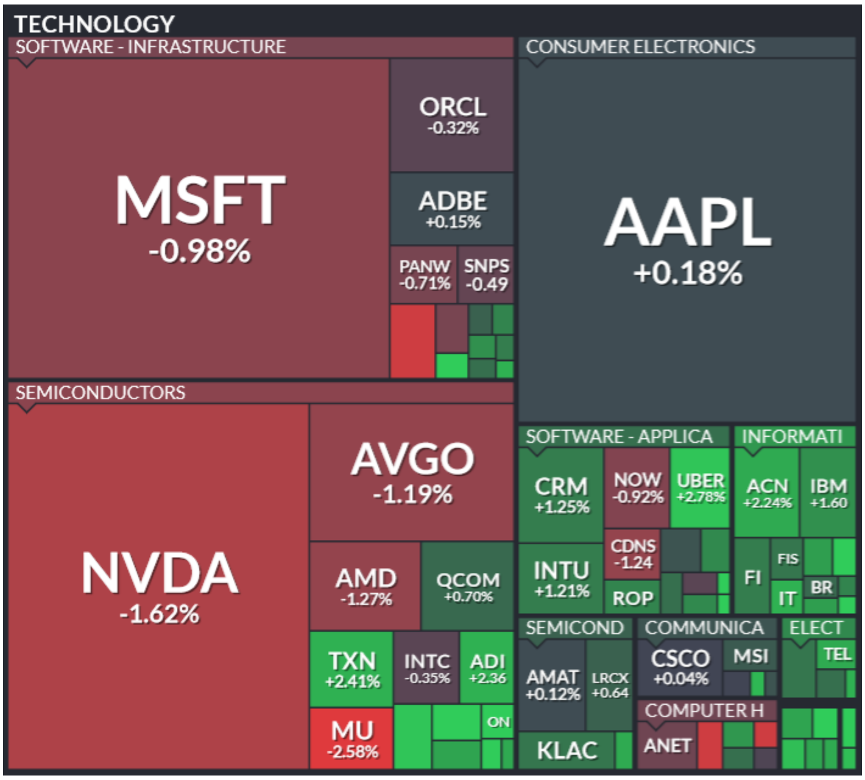

Fig 3. The Heat map of Us technology stocks [21].

Heat maps can also be used to analyze stock trading. Fig. 3 shows the heat map of US technology stocks. In the figure, green represents the rise of the stock, red represents the fall of the stock, and the higher the brightness of the color, the greater the rise or fall. Through the heat map, investors can easily see the situation of each stock, which is convenient for them to make quick judgments and decisions.

3.4. Limitations of Data Visualization and Ways to Improve It

In highly active markets, the timing diagram will become very complex, especially when showing multiple stocks or assets, where different lines may overlap, making the diagram difficult to distinguish. Under this situation, multiple charts or panels can be used to show different data sets separately to make sure the information won't overload. Also, for high-frequency data, data aggregation techniques such as average price per minute or second can be used to simplify the chart. In addition to this, a timing diagram may not be intuitive enough to show complex relationships between variables, like correlations between different assets. Advanced visualization techniques, such as parallel coordinate charts, network diagrams, or flow charts, are needed to show the multi-dimensional characteristics of trading data.

4. Conclusion

This paper provides a comprehensive review of the application and impact of high-frequency trading and algorithmic trading in financial markets. High-frequency trading, through high-speed trading technology and complex algorithms, has significantly improved market trading efficiency and liquidity, but it has also raised concerns about market stability and fairness. Algorithmic trading, by automating the execution of trading strategies, has reduced human intervention and enhanced trading accuracy and efficiency. Despite the immense potential of these trading methods in optimizing market operations, they also bring new risks and challenges, such as market volatility triggered by algorithmic errors and trading interruptions caused by technical failures. Therefore, regulatory sectors and market participants must work together to establish reasonable regulatory frameworks and risk management measures to ensure the healthy development of HFT and AT. Future research can further explore the optimization strategies and risk control methods of these trading methods to achieve the stability and sustainable development of financial markets.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

References

[1] Budish E, Cramton P, & Shim J. The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. The Quarterly Journal of Economics, 2020, 135(4), 1547–1629.

[2] Menkveld A J. High-Frequency Trading and its Impact on Markets. Annual Review of Financial Economics, 2022, 14, 93-113.

[3] Mizrach B, & Neely C J. Algorithmic Trading and Market Quality: Evidence from US Equities. Journal of Financial Markets, 2021, 55, 100578.

[4] Dakalbab F, Talib M A, Nasir Q, Saroufil T. Artificial intelligence techniques in financial trading: A systematic literature review. Journal of King Saud University - Computer and Information Sciences, 2024, 36(3), 102015.

[5] Chen M G. The Rise of Algorithmic Trading and Recent Research Progress. Institute of National Accounting, Beijing Normal University, Beijing, 2013, 100875.

[6] Addy W A, Ajayi-Nifise A O, Bello B G, Tula S T, Odeyemi O, Falaiye T. Machine learning in financial markets: A critical review of algorithmic trading and risk management. International Journal of Science and Research Archive, 2024, 11(01), pp. 1853–1862.

[7] Kirilenko A. High Frequency Traders and Asset Prices. Commodity Futures Trading Commission, 2018.

[8] Krishna J S, Panda A, Sindhuja P. Algorithmic Strategies in High-Frequency Trading: A Comprehensive Review. International Journal of Research Publication and Reviews, 2023, 4(11), 2460-2467.

[9] Zhang C. Quantified Strategies. Advanced Moving Average Strategies: Dual and Triple Moving Averages in Trend Following. Quantitative Trading Strategies Journal, 2023, 18(2), pp. 95-112.

[10] Wood J, Smith A, & Johnson R. Few-Shot Learning for Mean Reversion Strategies in Volatile Markets. Journal of Financial Data Science, 2023, 12(1), pp. 45-60.

[11] Gu S, Liu Y, & Wang J. Reinforcement Learning for Statistical Arbitrage: Advances and Applications. Quantitative Finance and Economics, 2023, 15(1), pp. 45-62.

[12] De Prado M L. Advances in Financial Machine Learning. Wiley, 2018.

[13] Liang C, Chen X, & Zhou G. High-Frequency Data and Machine Learning in Asset Pricing Models. Journal of Empirical Finance, 2023, 60(1), pp. 102-120.

[14] Wang T, Zhou L, & Huang R. Machine Learning Approaches for Extreme Risk Prediction in High-Frequency Trading. Risk Management and Financial Engineering, 2023, 12(4), pp. 215-230.

[15] Cartea Á, Jaimungal S, & Penalva J. Algorithmic and High-Frequency Trading. Cambridge University Press, 2015.

[16] Linton O, Mahmoodzadeh S. Implications of High-Frequency Trading for Security Markets. Annual Review of Economics, 2018, 10.1, pp. 237-259.

[17] Imen A B, Slaheddine H. High-frequency trading, stock volatility, and intraday crashes. Quarterly Review of Economics and Finance, 2022, 84, 337-344.

[18] Imen A B, Slaheddine H. Intraday interactions between high-frequency trading and price efficiency. Finance Research Letters, 2020, 41(prepublish):101862.

[19] Angel J J, McCabe D. Fairness in Financial Markets: The Case of High Frequency Trading. Journal of Business Ethics, 2013, 112(4): 585-595.

[20] Osis J, Donins U. in Topological UML Modeling, 2017.

[21] “Heat map of US technology stocks”, retrieved July 17, 2024, from https://finviz.com/map.ashx.